UNIVERSITY OF CALIFORNIA

Los Angeles

On the Stock Return Method to Determining Industry Substructure: Electronics, Petroleum, Banking, and Airlines

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Management

by

Seong-Ho Cho

1996

UMI Number: 9703820

The dissertation of Seong-Ho Cho is approved.

Marvin B. Lieberman

Marvin M. Lieberman

Elaine Mosakowski

Elaine Mosakowski

KeunKwan Ryu

KeunKwan Ryu

Bill McKelvey

Bill McKelvey, Committee Chair

University of California, Los Angeles

1996

To my teacher Bill McKelvey,
Wife Yeonsun,
And my parents, Dr. Koo-Yon Cho and Chung Shin Oh

Contents

List of Tables

Chapter 2

Chapter 3

Chapter 4

List of Exhibits

Chapter 2

Chapter 3

Chapter 4

ACKNOWLEDGMENTS

I would like to thank the members of my committee: Dr. Lieberman, Dr. Mosakowski, and Dr. Ryu for their support and guidance. Very specially, I wish to thank my advisor, Dr. McKelvey. Without his intellectual insights and encouragement (and sometimes wake-up calls), any accomplishments would not be possible. Any bit of my academic knowledge is thanks to my teachers.

I have never encountered a more stimulating or a supportive group than the strategy and organization faculty and doctoral students in the Anderson School at UCLA. Among the faculty, Jose de la Torre, William Ouchi, Richard Rumelt, Hans Schollhammer, Richard Goodman, and George Yip have all been wonderful mentors. I also thank Richard Roll and Ivo Welch in the finance for their intellectual insights. Among my fellow doctoral students I have found many wonderful friends who have provided invaluable support. I particularly wish to thank Doug Johnson, David Hoopes, and Anne Marie Knott.

Finally, I wish to thank my parents, Dr. Koo-Yon Cho and Chung Shin Oh, and my wife, Yeonsun Sohn, for their prayers. Their support and prayers have always provided me with enormous encouragement.

VITA

March 17, 1961	Born, Seoul, Korea
1984	B.A., Business Administration Korea University Seoul, Korea
1986	M.B.A., Management University of California, Los Angeles Los Angeles, California
1986-1987	Samsung Hewlett-Packard Seoul, Korea
1987	Research Assistant Massachusetts Institute of Technology Cambridge, Massachusetts
1988	Teaching Assistant Sloan School of Management Massachusetts Institute of Technology Cambridge, Massachusetts
1989	Citicorp, Investment Banking Group Seoul, Korea
1990-1992	Research Assistant Anderson Graduate School of Management University of California, Los Angeles Los Angeles, California
1993	Teaching Assistant Anderson Graduate School of Management University of California, Los Angeles Los Angeles, California
1995-1996	GTA Consulting Company Los Angeles, California

ABSTRACT OF THE DISSERTATION

On the Stock Return Method to Determining Industry Substructure:

Electronics, Petroleum, Banking, and Airlines

by

Seong-Ho Cho

Doctor of Philosophy in Management

University of California, Los Angeles, 1996

Professor Bill McKelvey, Chair

This dissertation proposes an objective and effective method of identifying industry substructure. Instead of using similar strategies, the stock return method classifies firms in an industry based on niche common variation of stock returns. The theoretical framework lies on the niche perturbation hypothesis coupled with niche theory. It is demonstrated that in the particular sample firms of electronics, banking, oil and airlines industries, the clusters derived from this method reflect structural differences with a good face and statistical validity. It is also claimed that subgroups identified by this method are objective and replicable. The potential applications of this method include a substitute for SIC-based classification, a method for analyzing longitudinal change in industry substructure, and a method for reference to the conventional methods.

Chapter 1

Introduction

This dissertation proposes an objective and effective method of subcategorizing firms in an industry. As noted by Caves and Porter (1977) and Porter (1980, 1985), firm structures vary within an industry because of mobility barriers. Recently, various theoretical explanations have been proposed for the existence of subgroups in an industry (Bogner, Mahoney, and Thomas, 1993). Empirical studies on subgrouping, however, have been limited by the quality of the methods used to detect and classify the subgroups (McGee and Thomas, 1986; Cool and Schendel, 1987; Mascarenhas and Aaker, 1989; Barney and Hoskisson, 1990). In their review of the strategic group literature, McGee and Thomas (1986) find that firm strategy is the most common basis for classifying industry subgroups. However, they note that, while firm strategy is complex and multidimensional, the choice of strategic dimensions used for determining subgroups is often limited and arbitrary. Barney and Hoskisson (1990) also conclude that the fundamental question of existence of strategic groups is not yet confirmed empirically despite many attempts. As an alternative to these methods based upon similar strategies, the stock return method is proposed and developed in this dissertation.

This dissertation consists of three chapters. Chapter 2 describes the stock return method and provides for the method's validity based on statistical evidences. In chapter 3, we resolve the issues of face validity and sampling window across different time spans. We also discuss the method's potential substitution for SIC-based grouping. In chapter 4, the stock return method is applied to the airline industry over the period from 1978 to 1992 in order to detect changes in its substructure. One motivation of chapter 4 is to enhance the validity of the stock return method by looking into longitudinal stability of subgroup structure over a longer time period. Since this dissertation is composed of three independent chapters aiming for independent publication, the presentation format of each chapter is structured as such. Thus, it appears that some parts are duplicating across chapters. Especially, a good portion of theory and method sections are repeating.

Chapter 2 presents the stock return method to identifying industry substructure, a similar approach first introduced by Ryans and Wittink (1985). As an alternative to strategy-based classification which is subject to researchers' arbitrary choice, the stock return method is presented as an objective and effective method. To support the claim's validity, 94 US electronic firms from Ulrich's data set (1979) are classified using weekly return data over 52 weeks. Then, a canonical discriminant analysis is conducted to confirm that the resulting clusters really exist (not artifactual) by using 67 independent taxonomic variables claimed by Ulrich to be evolutionarily significant characters. The results show that in our particular sample data structural patterns discernible from the stock return movements exist, and that an examination of stock return movements can provide insight into the structural differences among industry subgroups. In addition, industry subgroups found are statistically significantly different in terms of exogenous variables, suggesting that subgroups are not an artifactual statistical result.

Nonetheless, such a claim is made with some reservations. As acknowledged in chapter 2, these limitations may minimize the likelihood of the finding significant results, if in fact there is structure in the data. To address the identified limitations of chapter 2, in chapter 3, the stock return method is applied to the firms in the airline, oil, and banking industries to detect stable subgroups across different time spans.

Chapter 3 supports that the stock return method produces stable group classifications across different sample time spans. In our particular sample, the groups found demonstrate a clear face validity and as the time span increases from 1 year to 5 years, the group structures become clearer and tighter. The stability of groups found stays longitudinally maintained along these periods. In addition, our findings suggest that the stock return method detects stable industry-level effects over the several sample periods. Considering that the results of grouping are derived from objective 'hard' market returns over a 5 year time span, the consistencies of structural grouping results imply that the stock return data does bear the information of variance on critical attributes of firms and niches including industries. That is, stock returns seem to reflect variance on *any* reasonably relevant attribute, as long as there is change in the attribute that is noticed by security observers.

In chapter 4, the stock return method is further developed to analyze longitudinal structural dynamics. The method is extended from a static view to a dynamic one enabling us to analyze longitudinal change of industry substructure. Then, this method is applied to the airline industry over the period from 1978 to 1992. After groups are identified over time, these results are referenced with the industry's historical progress and accounting sales and income data. Our findings show that the stock return method can be an effective instrument to analyze longitudinal structural dynamics. In our particular sample, the results confirm the industry's historical progress, and the stability of results has been maintained along the long-term period.

Several conclusions can be drawn from these studies. One is that the stock return method can effectively identify industry subgroups. The findings from chapter 2 and 3 show that the groups found provide clear face validity and statistical validity, and the longitudinal consistency of subgrouping in chapter 4 provides for a high level of validity for using this method. The evidences from the three chapters confirm that industry substructure can be reliably and validly separated, and that substructure stability is longitudinally maintained over time. Although generalization can not be made, in our particular sample firms of electronics, banking and oil industries, the clusters derived from the stock return method reflect structural differences with a good face and statistical validity.

Another conclusion is that subgroups identified through the stock return method are objective and replicable. Conventional methods have not been able to necessarily achieve such goals mainly because choice of strategic dimensions used for determining subgroups is often limited and arbitrary. In the stock return method, subgroups are determined based on more objective and replicable market-driven equilibrium stock returns.

Other advantages of the stock return method over the conventional methods using strategic variables for classification include followings: First, stock return data are readily available and easily accessible. Second, this method does not require operationalization of assets and skills which determine structural differences. Third, stock return data are well documented over time, enabling feasibility for a longitudinal analysis. Fourth, measurement problems associated with accounting data are resolved.

Although primitive, this study promises the possibility of the stock return method as an alternative classification method to the method based on the SIC code. The SIC code has been the main approach to grouping firms in research dealing with different kinds of firms. Many observers have noted its limitations (Scherer, 1980). If the stock return method can provide better groupings than the SIC code, the quality of research on strategy and intra-industry studies would improve significantly because homogeneous grouping is critical to high quality results (McKelvey, 1982). Another application is to use subgroups identified by the stock return method as a reference to subgroups found by the conventional methods. For example, by conducting a canonical discriminant analysis based on a set of chosen strategic variables, one can find whether or not the chosen strategic dimensions are important determinants for industry substructure.

Chapter 2

On the Stock Return Method to Determining Industry Substructure: Electronics Industry

2.1 Introduction

> "...even if satisfactory a priori structure-conduct-performance hypotheses could be formulated, the scholar attempting to test those hypotheses would encounter serious obstacles. Much published information on business *conduct* [with author's emphasis] is incomplete and unreliable...Even if this last huddle could be surmounted, research penetrating the decision-making process of firm is so costly and time consuming that few company studies could be accomplished. One might be placed in the unhappy position of generalizing from an inadequate sample of special cases (Bain, 1959)" (Scherer, 1980: 6).

Since Caves and Porter (1977) and Porter (1980, 1985) introduce the concept of mobility barriers in explaining the performance differences among subgroups within an industry, many researches for over a decade have been devoted to further develop the framework and to empirically identify strategic groups based on similar strategies (*conduct*). However, such strategic group theory and empirical research have recently been challenged. McGee and Thomas (1986) and Barney and Hoskisson (1990) conclude that strategic group theory and its empirical research are limited, and that the fundamental question of existence of strategic groups is not yet confirmed empirically despite many attempts. They observe that "few concepts have caught the interest of strategic management theorists as much as the concept of strategic groups" (Barney and Hoskisson, 1990: 187). Nonetheless, they conclude that industry-level strategic group theory may be replaced by firm-level theoretical hypotheses like resource based hypotheses[1]. On the other hand, others including Bogner, Mahoney, and Thomas realize several logical weaknesses in strategic group theory and propose various alternatives advocating the existence of industry subgroups (or the importance of subgroup study).

In a review of empirical studies, McGee and Thomas (1986) find that firm strategy (conduct) is the most common basis for classifying industry subgroups. They note that while firm strategy is complex and multidimensional, the choice of strategic dimensions used for determining subgroups is often limited and arbitrary, and thus the groups found through the methods tend to be incomplete and non-replicable. Furthermore, Barney and Hoskisson (1990), Johnson (1995), and Cho and McKelvey (1996) find that while cluster analysis is mostly used to discover strategic groups, the statistical tests usually applied are all variants of the F-test which bases its test on minimized within-variance and maximized between-variance. Since by intention cluster algorithms group objects so that within-group variance is minimized and between-group variance is maximized, the statistical significance

---

[1] See: Wernerfelt, 1984; Teece, 1984; Barney, 1986, 1989, 1991; Rumelt, 1987; Reevis-Conner,

between groups using variants of the F-test cannot ensure the assertion that strategic groups actually exist. Thus, "the development of clusters [using cluster algorithms and variants of the F-test for statistical tests], per se, can not be used as a test of the existence of strategic groups" (Barney and Hoskisson, 1990: 189).

It appears that the lack of empirical findings to support the *strategic group hypotheses* has triggered redirection of research interests in the field. As Bain (1959) predicts, the scholars attempting to test these hypotheses have encountered serious obstacles. The failure of empirical tests has challenged the validity of strategic group hypotheses which used be one dominant framework for over a decade. Empirical failure, however, should not be considered as basis for proving these hypotheses invalid until some empirical evidence is provided. Furthermore, proposed alternative hypotheses should be tested to obtain their validity. Since the current empirical methods are ineffective, it seems imperative to develop an effective and replicable method.

This chapter presents the stock return method based on an analysis of movements in market security returns as an alternative to strategy-based classification. While it incorporates several improvements over the method initially developed by Ryans and Wittink (1985), the stock return method is claimed to be an objective and replicable method of identifying industry subgroups. To investigate whether or not the groups derived from the stock return method are artifactual (statistical significance), a canonical discriminant analysis is conducted with 67 taxonomic characters of sample firms. This test shows that industry subgroups found by this method are statistically significantly different in terms of exogenous variables, suggesting that groups found though the stock return method are not

---

1990; Sanchez, 1993; Teece, Pisano, and Schuen, 1994; Mosakowski and McKelvey, 1996.

from an artifactual statistical result.

The method of using stock returns has critical advantages over conventional methods of using strategic variables for classification. First, subgroups are determined based on market-driven equilibrium stock returns rather than on arbitrarily chosen strategic dimensions (by researchers), leading to groups that are more objective and replicable. Second, stock return data are readily available, and operational measurements for the security returns have been proven valid theoretically and empirically (Friedman, 1956; Fama,1976; Roll, 1977). In the conventional methods, operational measurements for chosen strategic variables are most likely hard to define and verifying their validity is difficult.

Section 2.2 reviews theoretical and empirical background. Section 2.3 discusses the ways in which the stock return method can be used for substructure and group identification. Section 2.4 describes the sample data and outlines the methodology. Results are discussed in section 2.5. Conclusions are presented in section 2.6.

2.2 Theoretical Background

2.2.1 Theoretical Development

Since Caves and Porter (1977) introduce the concept of "mobility barriers", many researches for over a decade have been devoted to identifying how mobility barriers create sustainable industry substructure and how such substructure is related to performance within subgroups (intragroup performance) as well as between subgroups (intergroup performance). Recently, strategic group theory based on mobility barriers has been challenged by resource based views of strategy partly because empirical findings fail to support the group-level theory. This firm-level theory draws on intrafirm resources to explain the basis for sustained competitive advantage or intrafirm performances (Wernerfelt, 1984; Teece, 1984; Barney, 1986, 1989, 1991; Rumelt, 1987; Reevis-Conner, 1990; Sanchez, 1993; Teece, Pisano, and Schuen, 1994; Mosakowski and McKelvey, 1996). While further development has been made in this avenue such as "core competence" (Prahalad and Hamel, 1990) and "dynamic capabilities" (Teece, Pisano, and Schuen, 1994), Barney and Hoskisson (1990) suggest the possibility that a firm-level substructure theory may replace industry-level group theory. Although debate is still inconclusive on whether resource based theory will replace or integrate with strategic group theory, this challenge induces a big problem for the group-level research.

In recognizing several logical weaknesses in strategic group theory based on mobility barriers, various alternatives advocating existence of substructure (or importance of subgroup study) have been proposed, all of which remain largely untested. Bogner, Mahoney, and Thomas (1993:11) note that "...under certain competitive scenarios, we should not expect performance differences across groups. Indeed, performance differences may be higher within strategic groups than across strategic groups." And later, "strategic groups can even exist in competition where mobility barriers are absent (e.g. spatial competition models and 'polymorphic equilibrium') (1993:13). Peteraf and Shanley (1993) also note that research on substructure has shifted away from its traditional focus on performance homogeneity toward *rivalry* (Cool and Dierickx, 1993; Peteraf, 1993; Porac and Thomas, 1994) and *cognitive taxonomy* (Rosch, 1978; Porac, Thomas and Emme, 1987; Porac, Thomas, and Baden-Fuller, 1989; Porac and Thomas, 1990; Reger, 1990; Porac, et al., 1993; Reger and Huff, 1993). Cho and McKelvey (1996:5-6) argue that "low within-group and high between-group performance variances may no longer be the "go or no-go" criteria for industry subgroup theory that they once were." In sum, the narrow performance orientation of strategic group theory has been broadened to include other theoretical bases for industry substructure. Major ones include the following (Bogner, Mahoney, and Thomas, 1993; Cho and McKelvey, 1996):

1. Strategic choice and endogenous mobility's barriers (Caves and Porter, 1977)

2. Different organizational structures determining different strategic behavior and the ability to execute strategies (Chandler, 1962)

3. Path dependencies of firms with different resource endowments and technologies responding to exogenous technological factors or changes in demand (Tang, 1988)

4. Lumpy market conditions (i.e. discrete niches), high transaction costs and sticky resources that influence later strategic behavior (Anderson and Lawless, 1993)

5. Spatial competition in which strategic group exists when sunk costs are relatively modest in a product differentiable market (Tang and Thomas, 1992)

6. Differential risk preferences and firm objectives (Baird, Sudharashan, and Thomas, 1988)

7. Game-theoretic formulations (Kumar, Thomas and Fiegenbaum, 1990)

8. Cognitive taxonomies (Porac and Thomas, 1990)

9. Ecological niche theory (Nelson, 1994)

Recently, *the ecological link* is recognized as an important basis of industry structure (Fombrun and Zajac, 1987; Porac, Thomas, and Baden-Fuller, 1989; Porac and Thomas, 1990; Peteraf and Shanley, 1993; Cho and McKelvey, 1996). More specifically, it is argued that industry substructure is determined by characteristics of the resource pool[2] commensurate with the niche[3] as well as competitors of resource in the pool. Given the resource pool and competitors in place in a niche, *essential competencies* defined as a set of a firm's harvesting capabilities that are crucial to its survival within a niche, are the sources which competitively draw revenues from market against competitors (Aldrich, 1979; McKelvey, 1982, 1994; Hannan and Freeman, 1989; Mosakowski and McKelvey, 1996). Noting that the nature of the resource gradients[4] is an important determinant of how firms achieve competitive advantage (i.e. via mobility barriers or via firms' resources)[5], Cho and McKelvey (1996) propose ecological niche perturbation hypothesis by

---

[2]In population ecology, environmental resources are generally defined as revenues, i.e., cash or kind, available in a niche, and they can be harvested by organizations depending upon their harvesting capabilities and competition structure within niche.

[3] Niche is defined as follows (Mosakowski and McKelvey ,1996): First, a niche is the "sum total of the adaptations of an organic unit" (Pianka, 1978: 238). A niche not only includes part of an organization's environment, but is also defined in part by the competencies the organization has available for harvesting the niche. Second, an occupying organization seldom, if ever, captures the full resource potential of a niche (because of incapabilities or competitors) (Hutchinson, 1957), meaning that further refining of its competency for harvesting is always possible. Third, it follows from this that while elements of an organization's niche are subject to manipulation as it develops relevant competencies, aspects of the broader environment, for all practical purpose, are not (McKelvey, 1982: 109). Fourth, the resource pool of a niche---generally defined as revenue both available and within an entity's competence for harvesting---is subject to change by events other than the behavior of its inhabitants, such as changing economic, technological, political and social elements. Fifth, resource pools co-evolve with the emergence of organizational forms suited for harvesting the resource. Finally, each niche contains other competitors who have also evolved along with the target firm and are able to compete more or less effectively for the resources.

[4] While a resource such as customer's willingness to pay a large sum to buy a car may appear in discrete intervals, usually a resource appears as a gradient along which customers are arranged according to some distribution such as Gaussian or uniform. Firms and competing groups may be also come to be distributed in a Gaussian or uniform manner as a result.

[5] Briefly, if niche is distributed in a Gaussian, rent generation process is via mobility barriers, while if in a uniform, rent generation process is via resource idiosyncrasy. See Cho and McKelvey (1996) for detailed discussion on the role of resource gradient for determining which theory (either strategic group theory based on mobility barriers or resource based theory) is most relevant as a cause of substructure.

incorporating the concept of "niche coevolution". This hypothesis suggests that efficiently surviving firms in a niche have similar survival capabilities and that any perturbations from inside and outside niche will similarly affect the harvesting potential and capabilities of firms in the group. Since it is a theoretical base for the stock return method in empirically identifying industry subgroups, in the following subsection, niche perturbation hypothesis will be presented.

2.2.2 Niche Perturbation Hypothesis

Niche perturbation hypothesis premises that the nature of the resource pool and the nature of firms coevolve and that *competition groups* may be identified by tracking changes in resource pool rather than trying to measure attributes of firms directly. If firms depend on the resource pool for their livelihood, that is, the availability of resource pools coevolves with the capabilities of firms for harvesting them, resource pool perturbations may act as a proxy measure for firm attributes.

The crucial assumption for this framework is *the fundamental interdependency between the nature of firms and the nature of niche resources available for harvesting* (McKelvey, 1982; Nelson, 1994; Cho and McKelvey, 1996). The nature of firms in a niche is characterized by their harvesting capabilities which may be different from their attributes. Some of the firm attributes may contribute to establishing harvesting capabilities which are directly related to firm performance[6]. For example, Harvard, Stanford, and MIT

---

[6] For instance, the creosote bush, apunta cactus, and joshua tree are similar in that they have desert survival capabilities (unlike ordinary plants), but each plant has totally different attributes. Some of the attributes like water-saving leaves or roots may enhance desert survival capabilities, but not all of the attributes do so.

have very different attributes (i.e. firm attributes). But each survives atop the same MBA education resource pool, and the harvesting capabilities of each school are efficient and similar. Supposing that some social and/or economical changes make MBA education in Cambridge very unattractive than in California, such change in the nature of niche resources available for harvesting will affect immediately the harvesting capabilities of each school. Thus, the competitive strengths of firms can not be identified without knowing what is in the niche to be harvested. On the other hand, supposing that UCLA and Cal Tech join the top three schools, such change in the nature of resident firms will affect immediately the MBA education resource pool. That is, what remains to be harvested is a function of the nature of resident firms. To sum, as firms within an industry compete for survival and growth, they change the nature of the niche resource pool they attempt to harvest. At the same time, as the niche changes, firms' harvesting capabilities also need to change if they are to compete effectively.

Based upon the fundamental interdependency between the nature of firms and the nature of niche resources available for harvesting, Cho and McKelvey (1996:13) define *competition groups* as comprising of firms having more or less equally effective survival capabilities for living off a common point on a resource gradient. If its harvesting capabilities are not roughly equal, a firm would not survive in the niche. Given similar survival capabilities (but not necessarily similar attributes), it follows that any actual or generally perceived or expected perturbation to the resource gradient (e. g. political, economic, environmental, technological, market, etc.) or niche competitor changes (e.g. a competing firm fails, or gains increased market share) will affect the nature of the resource gradients and availability of resources. At the same time, change in the resource gradients and availability of resources affects the harvesting potential and capabilities of firms in the group, and such change will influence the value of firms in the niche. In section 2.3, we will present the stock return method which uses change in stock returns of resident firms in a niche to identifying industry substructure.

2.2.3 Empirical Studies

Inspired by Porter's theoretical reasoning on the existence of structural differences among groups, empirical attempts have been made to identify subgroups in an industry. As reviewed by McGee and Thomas (1986), the most commonly used method is to examine the similar strategies in one or more functional areas. Some of the works using this method include the following; Hatten (1974) and Hatten and Schendel (1977), who use manufacturing, marketing and structural variables for grouping; Ramsler (1982) and Oster (1982), who classify subgroups on the basis of product strategies; Baird and Sudharsan (1983), who base their grouping on financial strategies such as leverage and dividend payment ratio; Hawes and Crittenden (1984) and Hatten and Hatten (1985), who look at marketing strategies including price and advertising; and Cool and Schendel (1987), who identify longitudinally strategic groups in the US pharmaceutical industry on the basis of strategic scope (e.g., range of market segments and geographic scope) and resource commitments (e.g., R&D and marketing strategy).

The main issues of empirical studies include (1) Does industry substructure exist?; and (2) Does firm performance depend on the strategic group within which a firm finds itself? As McGee and Thomas (1986) and Barney and Hoskisson (1990) note, most studies conclude that industry substructure exists. However, whether or not a firm's performance depends on strategic group membership is yet undetermined. Not to mention the inconclusive findings in (2), resource based theorists including Barney and Hoskisson (1990) criticize that empirical findings favoring to (1) do not necessarily provide solid evidences that industry substructure exists. It is argued that while strategic group theory requires that not only are there differences between firms in an industry but also that sets of firms in an industry implement similar strategies, most research to date ignores to check whether some degree of firm homogeneity in an industry exists (Barney and Hoskisson, 1990).

Furthermore, there are other criticisms related to the methods used to draw the conclusion of (1). First, while cluster analysis is most often used to discover strategic groups in an industry, the statistical tests usually applied are all variants of the *F*-test, which bases its test on minimized within-variance and maximized between-variance. Since by intention, cluster algorithms group objects so that within-group variance is minimized and between-group variance is maximized, the statistical significance between groups using variants of the *F*-test cannot ensure the assertion that strategic groups actually exist. Thus, "the development of clusters [using cluster algorithms and variants of the *F*-test for statistical tests], per se, can not be used as a test of the existence of strategic groups" (Barney and Hoskisson, 1990: 189). Cho and McKelvey (1996) note that the problem with tests of statistical significance in existing strategic group research is that they are strongly biased toward accepting as existing when in fact they do not, a Type I error --the null hypothesis being that subgroups do not exist.

Second, since groups are clustered based on input variables of arbitrarily chosen strategic dimensions, clusters found may result from the researcher's subjective choice of cluster variables (McGee and Thomas, 1986). Since firm strategy is complex and multidimensional, the choice of strategic dimensions used for determining subgroups is often limited and arbitrary. Arbitrary clustering variables undermine the correct and objective identification of industry subgroups.

Third, some classifications are based on firm strategy or "what they do" which is not only imitable, but changeable in nature. For example, Southwest Airline can decide to imitate Delta's strategy, and can actually pursue a similar strategy; however, they should not be categorized in the same group because their unique drivers and activities are fundamentally different. Mascarenhas and Aaker (1989) suggest that the use of elements of a firm's strategy as classifying variables may not be compatible with the search for nontransitory substructure because strategies are activities that may be easily imitated and changed. They propose clustering variables using assets and skills which systematically resist imitation and change.

Finally, clustering with a fragmentary choice of some functional strategies can not span a firm's structure. Because of externalities and complimentarities of factors comprising a firm's unique structure (Dierickx and Cool, 1989), a handful of elements of strategy or structure may not pick up overall structural differences.

In the following section, we present a method based on an analysis of movements in market security returns as an alternative to strategy-based classification for detecting structural difference among industry subgroups. This method overcomes the weaknesses shown to exist among previous methods of industry subgroup classification.

2.3 The Stock Return Method

2.3.1 Niche-Specific Effects and Covariant Stock Returns

The stock return method presumes that any niche perturbation will cause a spot-response in the stock returns (spot rates) of the resident competition group. As discussed in section 2.2.2 of niche perturbation hypothesis, any actual or generally perceived or expected perturbation to the resource gradient (e. g. political, economic, environmental, technological, market, etc.) or niche competitor changes (e.g. a competing firm fails, or gains increased market share) will affect the harvesting potential and capabilities of firms in the group, and thus the value of firms in the resident competition group will change accordingly. Then, under *the efficient market hypothesis* discussed in detail in section 2.3.2.1, the change in the value of firms resulting from niche perturbations will be reflected concurrently in their stock returns. If so, the variance of stock return residuals after eliminating systematic and industry risk will reflect niche-specific effects (see section 2.4.3.1), and examination of the residuals movement can detect the structural differences of industry subgroups.

The stock return method incorporates several conceptual and technical improvements over that used by Ryans and Wittink (1985) [7]. First, they claim that the movements of stock returns are directly related to group membership defined by common strategies, but there has been no evidence so far that the firms with similar stock movements adopt the same strategies. Second, Ryans and Wittink fail to offer sufficient statistical evidence to support the clusters found. Instead of using an arbitrary stopping rule in determining the statistically optimal number of clusters in data as Ryans and Wittink do, stopping rules which have been proven in the literature on clustering to be most effective are applied. Finally, a canonical discriminant analysis is conducted with 67 taxonomic characters of sample firms in order to investigate whether or not the groups

---

[7] In their study, Ryans and Wittink use US airline industry data from the CRSP data file, circa 1977-1979. They use the market model for obtaining residuals, and use both factor analysis and the "diameter " method of cluster analysis. Their choices as to number of factors or clusters are visual and subjective. In addition, statistical tests on whether the groups found are artifactual are not conducted. Their cluster results generally overlap the factor results, and from the point of face validity, the trunk airlines

derived from the stock return method are artifactual (statistical significance). The taxonomic characters used in this analysis have been identified as evolutionarily significant structural and organizational attributes in the electronics industry by Ulrich (1982) and Ulrich and McKelvey (1990).

2.3.2 Key Assumptions

2.3.2.1 Efficient Market Hypothesis

The stock return method assumes the efficient market hypothesis --- observed security returns "fully, correctly, and instantaneously" reflect all the publicly available information (Fama,1976; LeRoy, 1989; Fama and French, 1992). Any external niche shocks and resultant internal competitive impacts among niche resident firms will be "efficiently" reflected in their security prices via fierce market competition for arbitrage profit. Under this hypothesis, stock prices, and therefore stock returns[8] are accurate reflections of all available relevant information in the sense that self-interested rational arbitrageurs, recognizing that prices are out of equilibrium line, make a profit by buying or selling stocks, thereby driving prices back to equilibrium values consistent with available information (Ross, 1987; Huang and Litzenberger, 1988; LeRoy, 1989). Therefore, an incremental change in stock price is a market equilibrium valuation of the impact of disturbances on the underlying firm (Lucas, 1978; Huang and Litzenberger, 1988).

---

mostly are in the same cluster.

[8] We follow standard finance research practice in using “stock returns” rather than stock prices. Stock returns are derived from stock prices by taking into account dividend payments and stock splits (see Section 2.4.3 for detail).

Capital market efficiency has been a core tenet of finance theory since the 1960s. The key concept is that the capital market is "efficient" in the sense that all stock prices indicate the average positive returns which are equivalent investor's risk[9] (Merton, 1973; Fama, 1976; Lucas, 1978; Cornell and Roll, 1981; LeRoy, 1989; Fama and French, 1992). Fama (1965) shows that the serial correlation of one day changes in the natural logarithm of price are significantly different from zero and the correlations are positive. Alexander (1961) and Fama and Blume (1966) directly test the fair-game model by using the technical trading filter rule, and find that the capital market is allocatively efficient down to the level of transactions costs. Cornell and Roll (1981) also show that while it is reasonable to expect efficient markets where people can earn different gross rates of return, because they pay different costs for information, the net cost of their abnormal rates of return equals zero. These empirical tests show evidence that capital markets are efficient in their "weak form", meaning that no one can make a profit by using price-history information. This evidence implies that security returns "fully, correctly, and instantaneously" reflect all the publicly available information, the critical aspect as far as our method is concerned.

Why is the efficient market hypothesis critical? Under the efficient market hypothesis, the stock return is a market equilibrium valuation of underlying firms' assets (The role of stock return in the finance field is similar to that of product price in neoclassical microeconomics in the sense that price is a sufficient statistic which reflects an equilibrium valuation of an asset). A change of stock returns of firms competing in a particular niche reflects a reequilibration of the capital market's valuation of the underlying assets of firms

---

[9] In other words, stock market is an efficient submartingale or a fair game with positive returns

in the niche[10]. Furthermore, changes in security returns due to a niche perturbation represent a market equilibrium valuation on the impact on the underlying assets. Since efficiently surviving firms in a niche have similar survival capabilities and any perturbations from inside and outside niche will similarly affect the harvesting potential and capabilities of firms in the group (niche perturbation hypothesis), the impact from niche perturbations will be different across groups, and such difference should cause the market to reevaluate the assets of all the firms in the niche more or less simultaneously, and this reevaluation will, therefore, reflected "fully, correctly, and instantaneously" in their stock returns. This is why we can use stock returns to separate industry subgroup common variance from firm-specific and market-specific variances.

2.3.2.2 Nonperformance Component

Since they are phenotypic rather than genotypic measures, performance measures are not generally used as taxonomic characters in the taxonomic literature. Rather, characters which are closely related to survival or reproduction (i.e. core competence for organizations such as eating and reproduction parts for organisms) are used (Mayr, 1969 and McKelvey, 1982). Although it appears that the stock return method uses a performance measure (stock return) as a clustering character, this is not really the case. The stock return method is concerned with group level covariance resulting from niche perturbation, not the performance of individual firms. In an efficient capital market, the stock return response of firms in a particular niche, given a niche disturbance, will be

---

(Huang and Litzenberger, 1988).

[10] An interesting point made by Jaewoo lee is that the stock return method may not require a very stringent standard of market efficiency. Thus we do not need to be assured of instant reequilibration, only that attempts in this direction, in response to niche perturbations, produce niche related common variance.

instantaneously similar, but their performance is not necessarily similar. For our purpose, the performance measures are not used to detect clusters --only to show covariance in returns as an indication of their belonging to the same niche.

2.3.2.3 Nonaggregate Niche Effects

In order to use stock returns in combination with niche perturbations, the stock return method prerequisites that firms compete in specific nonaggregated niches, and the stock returns represent such nonaggregated effects. If a stock return were to represent the value of a diversified firm involving in multiple businesses across various niches, the representation of stock returns will be an aggregated one, and will obscure niche effects of interest. Consequently we will assume that disaggregated niche effects are required for the stock return method, and therefore select firms accordingly.

2.3.3 Advantages

The Ryans and Wittink (1985) stock return method offers a number of advantages for using stock returns in taxonomic analysis in general. A critical advantage of the methods using stock returns is that clusters found are objective and replicable. Since securities returns are 'hard' data determined by the efficient capital market, the data are objective and replicable. In the stock return method, the classification input variables are movements of such securities returns, and therefore, there is less room for researchers' subjective categorization or judgment about the classification input variables.

Another important advantage is that this method does not require choosing one or few from many descriptive attributes. Because the stock return is not a firm attribute at all---it is a market movement, and because it is not a narrow descriptive character, in the fashion of, say, kind of technology, number of hierarchical levels, level of niche resources, or number of businesses occupied, vast lists of taxonomic characters are avoided in favor of a single character, without losing overall representativeness[11]. Therefore, this method does not require to chose and operationalize attributes of assets and skills which determine structural differences. Finding objective measures for assets and skills is difficult: Mascarenhas and Aaker (1989), for example, tried to obtain the measures through extensive and costly field interviews.

Other advantages include the following: First, stock return data are readily available and easy to access. Second, stock return data are well documented over time, it is feasible to do a longitudinal analysis. Third, measurement problems associated with accounting data are resolved. The method does not need to use accounting data which is inherently susceptible to measurement error. Fisher and McGowan (1983) argue that accounting information may not be consistent from firm to firm or group to group, and that accounting rates of return, even if properly and consistently measured, provide almost no information about economic performance.

The major limitation of the stock return method is that firms diversified across industries would not be appropriate for clustering because the stock returns would reflect complex and combined responses from various business units across industries. However, many important industries are composed of basically single-industry firms. For example, steel, oil, aluminum, public utilities, airlines, office equipment, and banking

---

[11] Obviously, going from *n* characters down to 1 character is not the entire issue. We could take any single character as the basis of cluster analysis and then use *n-1* other characters for the canonical discriminant analysis. But, the stock return is not one of firm attributes or narrow descriptive characters. This is what is unique about this method.

industries are composed primarily (but not exclusively) of firms heavily committed to that one industry (Ryan and Wittink, 1985).

2.4 Method

2.4.1 The sample

94 US electronics companies are used for classification in this study. These sample firms are selected from 684 publicly held electronics firms in the United States as identified in the *1980 Electronic News Financial Fact Book and Directory.*

There are two screening criteria in order to qualify as a sample firm. First, the activities of the sample firms conform to Rumelt's specialization ratio of greater than 70 percent. Since they are involved in multiple businesses across industries and thus may represent their aggregated effects rather than nonaggregated niches, diversified firms, defined as less than 70 percent of Rumelt's measure, are screened out. Rumelt's measure of specialization is widely accepted in the field of business strategy[12], and firms with over 70 percent of specialization ratio are regarded as dominant single business firms (Rumelt, 1974, 1982). The sample firm's average specialization ratio is 0.89 with its standard deviation of 0.16, meaning that 89 percent of total sale is from a single business (see Table 2.1). This figure positively confirms the fact that they are highly specialized in a single business.

---

[12] Authors who have cited Rumelt's measure of specialization ratio include Montgomery and Singh (1984), Grant and Jammine (1988), and Ramanujam and Varadarajan (1989).

Second, electronics firms which are listed in the NASDAQ and have complete stock returns over the sample period in the University of Chicago's Center for Research in Security Prices (CRSP) data tapes are included in the sample data. The NASDAQ firms are generally smaller in size than those firms in the AMEX or NYSE, and they tend to concentrate on a single or fewer niches. The sample of 94 firms are highly specialized in one business, and they focus on one or fewer niches. Out of 60 defined niches in electronics industry, the sample firms are on average involved in only 4.17 niches (see Exhibit 2.3). Therefore, the industry substructure of firms in the NASDAQ is likely to be detected more effectively through stock return method.

2.4.2 Variables

For each company in the sample, a complete set of 52 weekly stock returns in 1979 and 67 numerical taxonomic characters[13] in the corresponding sample period are prepared for study. While the stock return method uses only stock returns for clustering, the 67 non-stock return variables are used for testing whether the clusters derived from the method are statistically significant structure.

As raw data, weekly returns are used rather than daily returns because weekly returns neutralize erroneous shocks. The variables used in the method are between-firm correlation coefficients of stock return residuals. Specifically, weekly stock return residuals (after eliminating systematic and industry risk) are correlated between the sample firms each week in 1979. The variables capture magnitudes and directions of instantaneous stock

---

[13] We thank David Ulrich for allowing us to use his data set. The data of the 67 taxonomic characters in this study are a subset of the data set used in his chapters (1982, 1990).

return movements reflecting disturbances over the sample period of 52 weeks. Since the method classifies groups on the basis of instantaneous stock response patterns, if some firms' stock return movement patterns are statistically significantly similar over 52 cases, they will be categorized in the same group.

The 67 numerical taxonomic characters are claimed to be evolutionarily significant characters by Ulrich (Ulrich, 1982, Ulrich and McKelvey, 1990). The taxonomic characters consist of 60 variables measuring the types of business/market competencies as well as 18 firm characteristic variables measuring firm size, macro productivity, and organizational diversification (see appendix 1). The variables of business/market competencies measure firms' presence in a niche(s) available in the industry. 60 niches or business/market competencies in the electronics industry are defined by Ulrich (1982) and Ulrich and McKelvey (1990) as the combinations of 10 product/market segments (components, power, industrial, instruments, communications, consumer-business, computer, government, transportation and nonelectronical) and 6 activities types (manufacture, sell, distribute, design-test, lease, and other). The typology of markets served by firms in the electronics industry evolves from existing typologies used by electronics analysts and industry associations and interviews and a delphi process with a panel of industry experts. Given that the rationale that organizational identity is a composite of work place and organizational competencies that produce a competitive product and service, the business competencies each firm drew upon to serve each market are added[14]. To avoid the effect of "conjoint absences"[15] (McKelvey, 1982:390), niche characters having no variance are deleted, leaving a total of 67 test characters.

2.4.3 Analytical Methods

In the following subsection, we will present methods for the stock return method. There are two phases for group identification. The first step is to obtain residuals from security returns, and the second is to manipulate the residuals so that meaningful clusters can be obtained.

Step I: Eliminating Systematic Movements

Phase I eliminates from total security returns systematic movements related to changes in the market index. Our interest lies in the spontaneous responses of the firm-specific portion of security returns. Firm-specific responses are partitioned from total returns via regression analysis.

The value-weighted market index from the NASDAQ is used for the market measure of the market movement that is common to all securities traded on exchange. The separation between firm-specific variation and market portfolio variation is done using the market model:

$$r_{i,T} = a_i + b_i\, r_{M,T} + e_{i,T} \qquad (1)$$

---

[14] Other authors who use the matrix of markets served by business competencies to analyze key characteristics of firm identity include Nathanson and Cassno (1982) and Hambrick and Lei (1985).

[15] A conjoint absence indicates that two entities may appear similar because they share the absence of some character.

where:

$r_{i,T}$ = weekly stock return for stock i on week T

or

$= (r_{i,t+1}+1) \times (r_{i,t+2}+1) \times ((r_{i,t+3}+1)) \times ((r_{i,t+4}+1)) \times ((r_{i,t+5}+1)+1) - 1,$

$t = 5(T-1)$, where $T = 1,2,3,...,50$

$r_{i,t}$ = daily stock return adjusted for stock split and dividend payment for stock i on day t

or

$= \{ p^*_{i,t} - p^*_{i,t-1} + d_{i,t} \} / p^*_{i,t-1}$

$p^*_{i,t}$ $= p_{i,t} \times s_{i,t}$, $s_{i,t}$ = coefficient for stock split adjustment

$r_{M,T}$ = weekly return on market portfolio (value weighted) at week T

a_i, b_i = coefficients in the model for stock i

$p_{i,t}$ = the price of security i on day t

$d_{i,t}$ = the dividend, if any, paid on day t for security i

$e_{i,T}$ = disturbance in the model for security i at week T

- this is normally distributed with mean 0 and variance q^2_i

i.e., $e_{i,T} \sim N[0, q^2_i]$.

This regression model estimates an intercept term (a_i) and the comovement (b_i) of individual security returns with the movement of the market index. Any variation due to factors not presented in the market portfolio will be captured in the disturbance term $e_{i,T}$.

The residuals from the market model regression are traditionally interpreted as abnormal returns --- the securities returns in excess of expected returns, or

$$AR_{i,T} = r_{i,T} - \{ a_i + b_i \, r_{M,T} \} \tag{2}$$

The residuals or weekly abnormal returns (WARs) reflect firm-specific variation including subgroup common variances, if any, and a noise term, and are 'free' of total market movement. When there exist significant niche perturbance resulting from mobility barriers, the residuals will reflect such group common variances or

$$AR_{i,T} = \alpha_{i,T} + \beta_{g,T} + \varepsilon_{i,T} \tag{2)'$$

where:

$\alpha_{i,T}$ = firm-specific factor for firm i at time T

$\beta_{g,T}$ = group-specific factor for group g at time T

$\varepsilon_{i,T}$ = disturbance in the model for security i at time T

- this is normally distributed with mean 0 and variance q'^2_i

i.e., $\varepsilon_{i,T} \sim N[0, q'^2_i]$.

Step II: Cluster Analysis of the Residuals

2.4.3.1 Resemblance Coefficient

The residuals from the market model are used to cluster groups in such a way that firms with similar directions and magnitudes of residual changes over the time span of sample data are grouped together. Specifically, the 52 WARs of each firm from the regression analysis are correspondingly correlated with those of another firm, and the correlation coefficient matrix between firms is used for a measure of directions and magnitudes of residual changes. Thus, the between-firm correlation coefficient or r_{ij} is a statistic which summarizes the closeness of abnormal return movements between firm *i* and firm *j* over the time span of 52 weeks. For example, if the abnormal returns of firm *i* and firm *j* move in the same direction and magnitude over the 52 weeks, the between-firm correlation coefficient will be 1 (Note that the between-firm correlation coefficient ranges from -1 to 1). Because the directions and magnitudes of spontaneous changes in stock returns per week are the basis for clusters, the between-firm correlation coefficient is a more effective statistic than others such as the Euclidean distance measure which captures absolute distance between residuals changes, but can not reflect their direction. Following convention in the finance literature, we use correlation coefficient as a resemblance coefficient.

The between-firm correlation coefficient is linearly transformed into a range of 0 to 2 without losing their ranking relationship. The linear transformation function is:

$$L(x) = -1 * (x - 1) \qquad (3)$$

where, x = between-firm correlation coefficient (-1 =< x =< 1)

The r_{ij} of 1, which means perfectly correlated movements of WARs between firm *i* and firm *j* over the 52 weeks, is transformed to 0; and the r_{ij} of -1, which means perfectly negatively correlated movements of WARs, is transformed to 2. Since this linear transformation is a one-to-one mapping, there is no information loss regarding the closeness of stock movements. The transformed between-firm correlation coefficient matrix becomes input distance data for cluster analysis.

It is hypothetically plausible to assume a special case of duopoly with zero-sum gain where two firms are competing for homogeneous products. Under this hypothetical situation, some shocks that are favorable for one firm, but unfavorable for another, may inversely affect the response of stock returns of the two firms[16], thereby suggesting that firms having a negative but strong correlation, i.e. r_{ij} of -1, should be grouped together as shown (3) in Exhibit 2.1. In our study, however, firms having a negative but strong correlation are regarded as less similar than firms having no correlation, i.e. r_{ij} of 0 as shown (1) in Exhibit 2.1. One rationale is that while stock returns reflect impacts from group common and/or firm-specific shocks (see section 3.2.2.2), in our particular sample firms, group common shocks which are embedded in stable niche characters may dominate firm-specific shocks (see equation (2)' in section 2.4.3). Our particular sample firms of electronics, banking, oil, and airline industry are not characterized by the situation of duopoly with zero-sum gain, and a firm's specific shocks are likely to influence minimally other competing firms. Another rationale is that even though impacts of firm-specific shocks are big enough, the duration of such impacts may be short because of other competitors' replication. An example may be the frequent fliers' mileage program launched first by American Airlines in 1981. In the same year, United counters with its own program, followed by TWA, Delta, Northwest, and Continental. On the other hand, since by definition, group common shocks are rooted in niche, replication is not possible in a short time.

[16] For example, Coke and Pepsi might show negative but strong correlation coefficient if shocks come from advertisements of either firm, whereas Coke and IBM are more likely show no correlation.

2.4.3.2 Clustering Algorithm

The Ward's (1963) minimum variance method is used for cluster analysis. In the Ward method, the distance between two clusters is the ANOVA sum of squares between two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation. The Ward method is chosen because it outperforms in every respect except the outlier problem other algorithms including centroid method (Kuiper and Fisher, 1975; Blashfield, 1976; Mojena, 1977; Milligan, 1980). In order to check Ward method's robustness to outliers, the outliers in the data (1, 3, 5, 7, 9 percent) are deleted, and the outcome with the deleted data is compared with that of total sample. This sensitivity test suggests that the Ward method is robust to the outlier with respect to this data[17].

2.4.3.3 Stopping Rules

In determining the number of clusters, we apply stopping rules that have proved to be the most effective in the literature: Pseudo F statistic (Calinski and Harabasz, 1974) and Pseudo T^2 statistic (Duda and Hart, 1973). Critical advantage of stopping rules over the dendogram analysis is that stopping rules are free from human subjectivity (Milligan and Cooper, 1985).

Pseudo F statistic (Calinski and Harabasz, 1974) is computed as [trace $\mathbf{B}/(k-1)$]/[trace $\mathbf{W}/(n-k)$] where n and k are the total number of samples and the number of clusters in the solution, respectively. The **B** and **W** terms are the between and pooled

---

[17] Up to 5 percent deletion, the outcomes are robust, and classification power increases. In 7 and 9

within cluster sum of squares and cross products matrices. Plainly speaking, Pseudo F is a sufficient statistic which can test a null hypothesis that k clusters are not statistically significantly different. Duda and Hart (1973) propose Pseudo T^2 statistic or $J_e(2)/J_e(1)$ where $J_e(2)$ is the sum of squared errors within cluster when the data is partitioned into two clusters, and $J_e(1)$ is the squared errors when only one cluster is present. Therefore, smaller Pseudo T^2 statistic represents that two partitions explain better than one cluster.

In an evaluation of 30 stopping rules which have appeared in the clustering literature, Milligan and Cooper (1985) conclude that the Calinski and Harabasz index (Pseudo F statistic) is the most effective, and the Duda and Hart statistic (Pseudo T^2 statistic) is the second most effective. Milligan and Cooper (1985) also show that if chosen correctly, stopping rules can effectively determine the correct number of clusters in data which possess distinct clusters.

2.4.3.4 Statistical Tests: Multivariate & Canonical Discriminant Analysis

In order to investigate whether or not the groups derived from the stock return method are artifactual (statistical significance), we conduct a canonical discriminant analysis with 67 taxonomic characters of sample firms. We achieve independence between grouping solution and test of statistical significance by applying statistical test on variables clearly independent from the stock return data. As mentioned in 3.3, the stock return is not a firm attribute or not a narrow descriptive character---it is a market movement. Therefore, cluster solution using taxonomic characters (list of multiple niche attributes) should be independent from that using stock returns (single variable).

---

percent deletion, the outcome becomes less robust, and classification power decreases.

Given grouping solution produced by the stock return method (4 clusters in this study) and 67 taxonomic characters of firms, the canonical discriminant procedures derive canonical functions (linear combinations of the taxonomic characters) that summarize between-class variation. The discriminant analysis also produces test statistics indicating whether the separation among stock return clusters is statistically significant (Hotelling, 1935, 1936; Waugh, 1942; Lawley, 1959; Kshirsargar, 1972; and Johnson and Wichern, 1988). If the test statistics show statistical significance, based on taxonomic characters which are exogenous to the movements of stock returns, we may conclude that the clusters resulting from the stock return method reflect statistically significant information about the industry substructure and that they are not artifactual results.

In addition, four multivariate statistics are calculated to test the hypothesis that separation of cluster means across 67 taxonomic characters of the Ulrich data are significant: Wilk's Lambda, Pillai's Trace, Hotelling-Lawley Trace, and Roy's Greatest Root (Pillai, 1960; Rao, 1973; Morrison, 1976). Significant F values for each multivariate statistic imply that the stock return method produces groups of firms that are different and reside in different niches.

2.5 Results

2.5.1 The Production of Residuals

After systematic variance is eliminated, the average WARs of the 94 firms is 0.000 with a standard deviation of 0.011. The normality test of the WARs suggests that they approximate a normal distribution. These results confirm the assumption on the disturbance in equation (1), and the WARs of each firm are normally distributed with mean 0 and variance q^2_i, i.e., $e_{i,T} \sim N[0, q^2_i]$.

Exhibit 2.2 shows movements of average WARs of 94 firms over the 52 weeks. Each movement of WARs i.e. from 1st week to 2nd week, etc., results from firm-specific variation across 94 firms during that period. Firm-specific variation may be derived from subgroup common variances, if any, and a noise term, and are 'free' of total market movement.

2.5.2 The Number of Groups

The pseudo F (Calinski and Harabasz, 1974) has the highest peak at 3 clusters (F=6.6) and the second highest peak at 4 clusters (F=6.2), and diminishes all the way after 5 clusters. The pseudo T^2 statistic (Duda and Hart, 1973) plunges from the highest peak of 6.5 (2 clusters) to the lowest value of 4.4 at 4 clusters, and bounces up to 4.7 (5 clusters) and 5.0 (6 clusters). These stopping rules strongly suggest that there are 3 or 4 groups in the data of the 94 electronics companies.

In this study, we take 4 groups as the optimal solution based on the following rationale. Although the pseudo F test indicates favorably 3 groups over 4 groups in this particular data, the pseudo T^2 test and visual dendogram analysis tilts our choice toward 4 clusters. In addition, the 4th group (n=19) in 4 cluster solution is diverged from the 1st group (n=36) in 3 cluster solution, indicating that the 1st group in 4 cluster solution is a subset of the 1st group in 3 cluster solution. Therefore, we conclude that analyzing 4 groups would provide better insights than analyzing 3 clusters. In any event, the canonical discriminant analysis produces statistically significant results for both 3 and 4 cluster solution, thus the choice of 4 clusters does not undermine our findings and implications of this chapter, which is to demonstrate a nonartifactual method of identifying industry substructure.

2.5.3 The Nature of the Clusters

2.5.3.1 Weekly Abnormal Returns Movement

In the following two subsections, we will present groups' specifications and niche presence. Note that while groups are clustered through stock returns, the specifications and niche presence of each group are based on the 67 independent Ulrich variables.

2.5.3.2 Group Specifications

As a way of offering some face validity to our findings, Table 2.1 describes firm characteristics of each group. One inference is that groups are distinguishable by their size. The firms in group 1 possess the largest total assets ($504.94 million) and number of employees (9,043), and are more than 10 times larger than firms in group 4. In terms of productivity, group 1 outperforms others in every aspect. Group 2 is doing better than group 3 marginally. Group 4 achieves comparable productivity per unit dollar of assets and person, but it is far behind in ROA and ROE.

With respect to organizational diversification, the average specialization ratio (percent of sales in leading line of business) and electronics specialization ratio (percent of sales in leading line of electronics business) for the 94 sample are 0.89 and 1.95, respectively. These high ratios indicate that the sample firms are concentrated and focused on fewer niches.

2.5.3.3 Niche Presence

Exhibit 2.2 shows in which of the 60 business/market niches, defined by Ulrich (1982) and Ulrich and McKelvey (1990), the firms of each group show dominant presence. The columns of the niche matrix represent activities (component, power, computers, etc.) and the rows represent product/market segments (manufacturing, distribution, R&D, etc.).

In terms of activities types, each group is mostly involved in manufacturing, marketing, and R&D activities, and there is little presence in distribution, lease and other activities. Although group 2 is more heavily involved in manufacturing (55 out of 126 or 44%), activities types appear to be more or less similar across groups. With respect to product/market segments, there are distinctive differences among groups. Group 1 is highly involved in instruments (23%), and its presence in non-electronics (15%) and transportation (11%) is the highest among groups. In Group 2, its presence in component segment (21%) is among the highest. They are also active in instruments (17%) and computers (17%). Group 3 is highly involved in industrial segment (19%) and is also active in computers (18%). Finally, Group 4 is highly concentrated on computers (34%) and components (27%) in its niche presence, and its involvement in computers segment is the highest among groups. Groups 1 and 3 are more or less evenly spread across a number of lesser product/market segment involvement. Group 4 is more focused with two strong involvements.

2.5.4 Testing for Statistically Significant Structure

Even though univariate description of each group provides good insight into the group discrepancies, it is not sufficient to conclude that the groups are statistically significantly distinguishable from each other. Since group differences are multidimensional, statistical inferences should be made based upon multivariate analysis. Although the descriptive information in Table 2.1 and Exhibit 2.3 provides modest insight into differences among the groups, it does not give a clear face validity.

In the canonical discriminant analysis based on the 67 taxonomic characters and the four clusters found from the stock return method, 3 canonical discriminant functions are derived. As shown in Table 2.2, the canonical coefficients for the first canonical variable, CAN1, have a robust discriminatory power (based on $R^2 = 0.84$) for separating classes, with an eigenvalue of 5.37[18]. CAN2 has an R^2 of 0.79 with its eigenvalue of 3.76, while CAN3 has an R^2 of 0.71 and its eigenvalue of 2.48. CAN 1 explains 46 percent of the total common variance.

The results of multivariate analysis confirm that all possible differences among the means of the four clusters are statistically significantly different across the 67 independent taxonomic characters as shown in Table 2.3a. Wilks' Lambda is 0.010 with F-statistic of 1.43 ($p = 0.037$). Pillai's Trace is 2.345, with $F = 1.47$ ($p = 0.025$). Hoelling-Lawley Trace is 11.602, with F-value of 1.39 ($p = 0.056$). Roy's Greatest Root is 5.366, with $F = 2.20$ ($p = 0.013$). In three of the four tests the results of the canonical discriminant analysis are clearly significant, with the fourth test only slightly over the $p < 0.05$ confidence level.

---

[18] Eigenvalue can be interpreted as the ratio of between-canonical correlation to pooled within-class variation for the corresponding canonical variable. As a rule of thumb, eigenvalue greater than one is regarded significant.

Exhibit 2.4 shows the graphical plot of the firms based upon the canonical scores of firms in each class (The number represents their group identification). As shown in Table 2.3b, the F statistic for the null hypothesis that the canonical correlation of the first canonical discriminant function and all smaller ones are zero in population is 1.43 ($p = 0.037$), and the null hypothesis can not be accepted. On the other hand, the F tests for the second and third canonical discriminant functions suggest that their canonical correlations with class variable can not statistically be non-zero in population ($p = 0.1826$ and $p = 0.6560$, respectively). Given that only CAN1 function is significant, we show only the plot with respect to CAN1 and CAN2. It shows the separation among the four groups rather clearly, so the other plots are redundant for our purposes.

An interesting finding is that CAN1, the only significant function, is not related with size variables listed in Table 2.1. As shown in Appendix 2 where the top 20 characters of CAN1 and CAN2 are listed, the dominant variables on CAN1 are the niche characters such as industrial-manufacturing (-0.958), consumer-leasing (-0.920), and nonelectrical-distribution (0.912). Among the most dominant four characters (weights of 0.9 or higher), there is only one firm character of total assets per employee (0.988). Many of the size characters are loaded in CAN2. We have anticipated that the size characters might "drive" the solution (and frequently taxonomists avoid size characters for this reason (McKelvey, 1982)). This finding suggests that the grouping solution from the stock return method is not significantly influenced by the size characters.

2.6 Discussion and Conclusion

This study tests the premise that analysis of stock return movement can reveal the structural differences among industry subgroups. It is claimed that the stock return method is an objective and replicable method to identify industry subgroups. In this method, subgroups are determined based on market-driven equilibrium stock returns rather than on arbitrarily chosen strategic dimensions (by researchers), leading to groups that are more objective and replicable. It is also claimed that groups found though the stock return method are not an artifactual statistical result.

In order to test the validity of the premises of the stock return method, 94 electronics firms listed in the NASDAQ are used for study. From the stock return data, market and industry effects are removed through the market regression model. Using product-moment resemblance coefficients, Ward's clustering method, and analytical stopping rules, we identify four subgroups in our particular sample data. Specifically, the direction and magnitude of a firm's weekly abnormal returns are analyzed to classify firms with similar patterns into the same subgroup. Therefore, the firms in a cluster have homogeneous patterns of abnormal stock returns movements, and such patterns are distinguishable from those in other clusters. In order to test whether or not the clusters found in this method are artifactual, a canonical discriminant analysis and face validity check have been conducted based on the 67 independent characters of Ulrich data. A plot of the location of the 94 firms in terms of the first and second discriminant functions show four obviously distinctive groups. In addition, statistical tests show that the groups found by the stock return method are statistically different across the 67 independent variables.

There are some limitations in the study. First, although statistically significantly different, the groups found in the study fail to provide a clear face validity mainly because the sample firms are not well-defined enough to be familiar to readers. The sample firms used in the study are a subset of all electronics companies; only 94 firms are included out of publicly held 684 firms in the industry. This fact may induce distortion of clusters found, and impede industrywide inferences on the industry substructure. Furthermore, the groups found cannot demonstrate clear groupings for the purpose of face validity. For this exploratory study, however, the sample firms in the electronics industry are chosen primarily because of the availability of the 67 independent variables for canonical discriminant analysis. Second, a one-year sample window may be too short of a time to fully reflect significant niche disturbances. Without understanding of how the choice of a sample window affects optimal grouping, our findings may be limited. Third, the clustering method does not allocate observations to clusters randomly (no available clustering package does). This fact may generate locally optimized clusters rather than globally optimized clusters.

Despite the limitations, conclusions can be drawn from the study. One is that the stock return method is an effective method to identify industry substructure, and groups found are not an artifactual statistical result. There are structural patterns discernible from the stock return movements of the firms in the electronics industry, and an examination of stock return movements can provide an insight into the structural differences among industry subgroups. The results from the canonical discriminant analysis show that the stock return method can effectively and efficiently reveal structures which are consistent with those structures based on the 67 taxonomic characteristics (note that taxonomic variables are independent from stock returns, and that they are obtained through costly and time consuming interviewing process). Furthermore, this test shows that groups found though this method are not an artifactual statistical result.

Another conclusion is that subgroups identified through the stock return method are objective and replicable. While objectivity and replicability are important objectives in classification, the conventional methods have not necessarily achieved such goals mainly because choice of strategic dimensions used for determining subgroups is often limited and arbitrary. In the stock return method, subgroups are determined based on 'hard' stock return data and few choices are given to researchers in implementing this method.

Since this study demonstrates that the stock return method is an effective method, we believe that resolving the identified limitations is rewarding and imperative. Immediate future studies should include following improvements:

1. *Face Validity.* Although the statistical validity of the stock return method is clear in terms of exogenous niche variables, its face validity seems not yet satisfactory in chapter 2. It is necessary to show face validity.

2. *Small window.* Instead of one year of data collection, 1979, which may be too short of a time to pick up many significant niche disturbances. It should be tested whether or not the stock return method is valid when time span is extended from 1 year to a longer period.

3. *Unknown stability.* This study does not consider the evolutionary dynamics of industry subgroups over a longer time horizon. Future study needs to check the stability of the substructure over the life of the population.

4. *Specialization.* While the sample of this study only includes 94 firms out of the 684 electronics firms, future study needs to include all of the available firms in an industry.

5. *Size.* Instead of using small firms within a target population, future study needs to use sample consisting of the largest firms in an industry.

In addition to attempting to resolve these limitations, one should also make sure that the grouping results are not artifactual. Because the F test (or its kind) base their tests on minimized within variance and maximized between variance, statistical significance tests based on the cluster/F test approach will make a Type I error. Future studies should incorporate some schema so that the results may avoid these artifactual problems.

Chapter 3

On the Stock Return Method to Determining Industry Substructure: Case of Airline, Oil, and Banking Industries

3.1 Introduction

Since firm structures vary within an industry (Caves and Porter, 1977; Porter, 1980, 1985; Cool and Dierickx, 1993; Peteraf, 1993; Peteraf and Shanley, 1993; Porac and Thomas, 1994), it is important to subcategorize the firms in an industry in an objective and effective way (Hunt, 1972; Newman, 1973, 1978; McGee and Thomas, 1986; Hatten and Hatten, 1987; Barney and Hoskisson, 1990; Tang and Thomas, 1992; Bogner, Mahoney, and Thomas, 1993). However, empirical methods of classifying industry subgroups have recently been challenged. McGee and Thomas (1986) conclude that the choice of strategic dimensions used for determining subgroups is often limited and arbitrary, resulting in incomplete and non-replicable groupings. Barney and Hoskisson (1990) also argue that because of failure of testing statistical significance between groups, the fundamental question of existence of strategic groups is not yet confirmed empirically.

As an effort to resolve the identified problems, in chapter 2, the stock return method is proposed as an objective and effective method in classifying industry substructure. Chapter 2 supports such a claim by demonstrating that industry subgroups found by this method are statistically significantly different in terms of exogenous variables while avoiding any artifactual statistical results. Such a claim, however, is made with some reservations.

One limitation of chapter 2 is that groups found have little face validity. This is mainly because the sample of electronic firms are not familiar to the average reader. They were chosen as a sample only to test nonartifactual statistical significance of the stock return method by using available exogenous variables. Another limitation of chapter 2 is that the sample period is limited to a rather arbitrary one year period (1979). A one-year sample window may be too short of a time to fully capture important disturbances. Furthermore, it is implicitly assumed that the chosen sample window is within one stable time period. Although they stem from utilizing the available data for the exogenous variables which are the source for testing nonartifactual statistical significance, as acknowledged in the chapter, these limitations may act to minimize the likelihood of the finding significant results, if they in fact exist.

The purpose of this chapter is to further develop the stock return method by resolving the limitations of face validity and sampling window identified in chapter 2, and to discuss its potential substitution for the SIC-based grouping. In our study, the sample window period is extended from the previous one year window to 4 different windows, namely 1-year, 2-year, 3-year, and 5-year window spans. The grouping results from the different windows are then analyzed to determine the effectiveness of the stock return method. Sample firms are deliberately chosen from industries composed of basically single-industry firms (Ryan and Wittink, 1985), namely the airline, oil, and banking industries so that the effects from external disturbances will be homogeneous by industry and industry subgroups. By applying the method to obviously distinct samples, we resolve the issue of weak face validity. By formally applying different sample windows, the limitations of *small window* and *unknown stability* are also discounted.

In our particular sample, the groups found show a clear face validity, and the stability of groups is maintained within these periods. Furthermore, we find that the method may detect stable industry effects in addition to subindustry effects. Over the sample periods, distinctive industry structure has been identified and sustained. Based on our findings, we conclude that the stock return method produces stable group classifications across different sample time windows. Given that objectivity and replicability are crucial in empirical studies, the stock return method may introduce a way to enhance the level of objectivity and replicability in the strategic group research methods. Potentially, the stock return method may provide more homogeneous groupings than the SIC-based classification, and if true, it will generally boost the quality of research on strategy and competitive organizing questions.

In section 3.2, we review the theoretical background. Section 3.3 describes the sample data and outlines the methodology. Results are discussed in section 3.4. Discussion and conclusions are presented in section 3.5.

3.2 Theoretical Background

The theoretical basis of the stock return method for why industry subgroups or structural asymmetry exists is *niche perturbation hypothesis* (Cho and McKelvey, 1996). In the following subsection, we will present the theoretical reasoning underlying this hypothesis.

3.2.1 Niche Perturbation Hypothesis

In this framework, industry substructure is determined by characteristics of the resource pool[19] commensurate with the niche[20] as well as competitors of resource in the pool. Given the resource pool and competitors in place in a niche, firms who possess essential competencies (harvesting capabilities that are crucial to its survival within a niche) can only draw revenues competitively from market against competitors (Aldrich, 1979; McKelvey, 1982, 1994; Hannan and Freeman, 1989; Mosakowski and McKelvey, 1996). Then, in equilibrium, efficiently surviving firms in a niche will have similar survival capabilities (competition groups) and any perturbations from inside and outside niche will similarly affect the harvesting potential and capabilities of firms in the group.

The crucial assumption of this hypothesis is the fundamental interdependency

---

[19]In population ecology, environmental resources are generally defined as revenues, i.e., cash or kind, available in a niche, and they can be harvested by organizations depending upon their harvesting capabilities and competition structure within niche.

[20] Niche is defined as follows (Mosakowski and McKelvey ,1996): First, a niche is the "sum total of the adaptations of an organic unit" (Pianka, 1978: 238). A niche not only includes part of an organization's environment, but is also defined in part by the competencies the organization has available for harvesting the niche. Second, an occupying organization seldom, if ever, captures the full resource potential of a niche (because of incapabilities or competitors) (Hutchinson, 1957), meaning that further refining of its competency for harvesting is always possible. Third, it follows from this that while elements of an organization's niche are subject to manipulation as it develops relevant competencies, aspects of the broader environment, for all practical purpose, are not (McKelvey, 1982: 109). Fourth, the resource pool of a niche---generally defined as revenue both available and within an entity's competence for harvesting---is subject to change by events other than the behavior of its inhabitants, such as changing economic, technological, political and social elements. Fifth, resource pools co-evolve with the emergence of organizational forms suited for harvesting the resource. Finally, each niche contains other competitors who have also evolved along with the target firm and are able to compete more or less effectively for the resources.

between the nature of firms and the nature of niche resources available for harvesting (McKelvey, 1982; Nelson, 1994; Cho and McKelvey, 1996). The nature of firms in a niche is characterized by their harvesting capabilities. As firms within an industry compete for survival and growth, they change the nature of the niche resource pool they attempt to harvest. At the same time, as the niche changes, firms' harvesting capabilities also need to change if they are to compete effectively. Based upon this fundamental interdependency assumption, Cho and McKelvey (1996:13) define *competition groups* as comprising of firms having more or less equally effective survival capabilities for living off a common point on a resource gradient. If its harvesting capabilities are not roughly equal, a firm would not survive in the niche. Given similar survival capabilities (but not necessarily similar attributes), it follows that any actual or generally perceived or expected perturbation to the resource gradient (e. g. political, economic, environmental, technological, market, etc.) or niche competitor changes (e.g. a competing firm fails, or gains increased market share) will affect the nature of the resource gradients and availability of resources. At the same time, change in the resource gradients and availability of resources affects the harvesting potential and capabilities of firms in the group, and such change will influence the value of firms in the niche.

Another important aspect of this hypothesis is that competition groups may be identified by tracking changes in resource pool rather than trying to measure attributes of firms directly. If firms depend on the resource pool for their livelihood, that is, the availability of resource pools coevolves with the capabilities of firms for harvesting them, resource pool perturbations may act as a proxy measure for firm attributes (Cho and McKelvey, 1996).

3.2.2 The Stock Return Method

3.2.2.1 Key Assumption: Efficient Market Hypothesis

The stock return method assumes the efficient market hypothesis --- observed security returns "fully, correctly, and instantaneously" reflect all the publicly available information (Fama,1976; LeRoy, 1989; Fama and French, 1992). Any external niche shocks and resultant internal competitive impacts among niche resident firms will be "efficiently" reflected in their security prices via fierce market competition for arbitrage profit. Under this hypothesis, stock prices, and therefore stock returns[21] are accurate reflections of all available relevant information in the sense that self-interested rational arbitrageurs, recognizing that prices are out of equilibrium line, make a profit by buying or selling stocks, thereby driving prices back to equilibrium values consistent with available information (Ross, 1987; Huang and Litzenberger, 1988; LeRoy, 1989). Therefore, an incremental change in stock price is a market equilibrium valuation of the impact of disturbances on the underlying firm (Lucas, 1978; Huang and Litzenberger, 1988).

Under the efficient market hypothesis, the stock return is a market equilibrium valuation of underlying firms' assets. A change of stock returns of firms competing in a particular niche reflects a reequilibration of the capital market's valuation of the underlying assets of firms in the niche[22]. Furthermore, changes in security returns due to a niche

---

[21] We follow standard finance research practice in using "stock returns" rather than stock prices. Stock returns are derived from stock prices by taking into account dividend payments and stock splits (see Section 3.3.3.1 for detail).

[22] An interesting point made by Jaewoo lee is that the stock return method may not require a very stringent standard of market efficiency. Thus we do not need to be assured of instant reequilibration, only

perturbation represent a market equilibrium valuation on the impact on the underlying assets. Since efficiently surviving firms in a niche have similar survival capabilities and any perturbations from inside and outside niche will similarly affect the harvesting potential and capabilities of firms in the group (niche perturbation hypothesis), the impact from niche perturbations will be different across groups, and such difference should cause the market to reevaluate the assets of all the firms in the niche more or less simultaneously, and this reevaluation will, therefore, reflected "fully, correctly, and instantaneously" in their stock returns. This is why we can use stock returns to separate industry subgroup common variance from firm-specific and market-specific variances.

3.2.2.2 Niche-Specific Effects and Covariant Stock returns

The stock return method presumes that any niche perturbation will cause a spot-response in the stock returns (spot rates) of the resident competition group. Any actual or generally perceived or expected perturbation to the resource gradient (e. g. political, economic, environmental, technological, market, etc.) or niche competitor changes (e.g. a competing firm fails, or gains increased market share) will affect the harvesting potential and capabilities of firms in the group, and thus the value of firms in the resident competition group will change accordingly. Then, under the efficient market hypothesis, the change in the value of firms resulting from niche perturbations will be reflected concurrently in their stock returns. Therefore, if there exist industry- or group- common variations derived from niche disturbances, such common variations may induce different spot-responses in stock returns (spot rates) across industries or groups within an industry.

---

that attempts in this direction, in response to niche perturbations, produce niche related common variance.

In order to capture industry- and group-common variations, systematic (market) variance is eliminated from the total variance. Once the systematic risk is removed, the variance of residuals may represent individual risk as well as industry and/or group membership risk. Residual variations after eliminating market variation from total variation are as follows (see equation (2) and (2') in section 3.3.3.1):

Residual Variations = Total Variations - Market Variations, or

= Industry Variation + Group Variations + Error Term

By definition, the error term is random. If residuals of stock returns show common variations significantly over time, we can infer that there exist variations from industry- and/or group-common disturbances. Without industry- and/or group-common variations, by definition, residual variations should be random, and common variations should not be identified systematically and persistently over time.

Assuming that efficient stock market hypothesis holds, the fact that there exist common stock return comovements, guarantees that there have been a *sufficient* number of group-common shocks in the environment, and those shocks have been *significant*. Thus, the stock return method does not require a check, *a priori*, as to whether there are significant numbers in group-common shocks and corresponding impacts.

The stock return method examines the movement of stock return residuals after eliminating market and industry variance in order to detect the structural differences of industry subgroups. If stock return residuals of some firms in an industry move similarly while those of other firms do not, we may then infer that group-common variations exist.

3.2.2.3 Remarks on the Stock Return Method

Nonperformance Component

Since they are phenotypic rather than genotypic measures, performance measures are not generally used as taxonomic characters in the taxonomic literature. Rather, characters which are closely related to survival or reproduction (i.e. core competence for organizations such as eating and reproduction parts for organisms) are used (Mayr, 1969 and McKelvey, 1982). Although it appears that the stock return method uses a performance measure (stock return) as a clustering character, this is not really the case. The stock return method is concerned with group level covariance resulting from niche perturbation, not the performance of individual firms. In an efficient capital market, the stock return response of firms in a particular niche to a niche disturbance may be instantaneously similar, but their performance is not necessarily similar. For our purpose, the performance measures are not used to detect clusters --only to show covariance in returns as an indication of their belonging to the same niche.

Nonaggregate Niche Effects

In order to use stock returns in combination with niche perturbations, the stock return method prerequisites that firms compete in specific nonaggregated niches, and the stock returns represent such nonaggregated effects. If a stock return were to represent the value of a diversified firm involving in multiple businesses across various niches, the representation of stock returns will be an aggregated one, and will obscure niche effects of interest. Consequently we will assume that disaggregated niche effects are required for the stock return method, and therefore select firms accordingly.

3.2.2.4 Advantages

The Ryans and Wittink (1985) stock return method offers a number of advantages for using stock returns in taxonomic analysis in general. A critical advantage is that clusters found are objective and replicable since securities returns are 'hard' data determined by the efficient capital market. There is little room for researchers' subjective categorization or judgment about the classification input variables. Another advantage is that this method does not require choosing one or few from many descriptive attributes. Because the stock return is not a firm attribute at all---it is a market movement, and because it is not a narrow descriptive character, in the fashion of, say, kind of technology, number of hierarchical levels, level of niche resources, or number of businesses occupied, vast lists of taxonomic characters are avoided in favor of a single character, without losing overall representativeness[23]. Therefore, this method does not require to chose and operationalize attributes of assets and skills which determine structural differences. Finding objective measures for assets and skills is difficult: Mascarenhas and Aaker (1989), for example, tried to obtain the measures through extensive and costly field interviews.

Other advantages include the following: First, stock return data are readily available and easily accessible. Second, since stock return data are well documented over time, it is feasible to do a longitudinal analysis. Third, measurement problems associated with accounting data are resolved. The method does not need to use accounting data which is inherently susceptible to measurement error. Fisher and McGowan (1983) argue that

---

[23] Obviously, going from *n* characters down to 1 character is not the entire issue. We could take any single character as the basis of cluster analysis and then use *n-1* other characters for the canonical discriminant analysis. But, the stock return is not one of firm attributes or narrow descriptive characters. This is what is unique about this method.

accounting information may not be consistent from firm to firm or group to group, and that accounting rates of return, even if properly and consistently measured, provide almost no information about economic performance.

The stock return method has some limitations. The major limitation of this method is that firms diversified across industries are not appropriate for clustering because the stock returns would reflect complex and combined responses from various business units across industries. However, many important industries are composed of basically single-industry firms. For example, steel, oil, aluminum, public utilities, airlines, office equipment, and banking industries are composed primarily (but not exclusively) of firms heavily committed to that one industry (Ryan and Wittink, 1985).

In this chapter, the stock return method is further developed by resolving the identified limitations in chapter 2. Specifically, the limitations to be resolved are as follows:

1. *Face Validity.* Although the statistical validity of the stock return method is clear in terms of exogenous niche variables, its face validity seems not yet satisfactory in chapter 2. This chapter seeks the face validity of the method.

2. *Small window.* Instead of one year of data collection, 1979, which may be too short of a time to pick up many significant niche disturbances, we use up to 5 years of data. As shown in section 3.4, as the time span increases from 1 year to 5 years, the group structures become clearer and tighter, implying that more of the significant niche perturbations would increase the effectiveness of classification.

3. *Unknown stability.* Previous study does not consider the evolutionary dynamics of industry subgroups over a longer time horizon. Unlike Fiegenbaum and Thomas (1993), the previous study has not assured that its data are from only one stable time period in the life of the population. This study has checked the stability of the populations within the window spans.

4. *Specialization.* While the sample of the previous study only includes 94 of the 684 publicly held electronics firms in the United States (circa 1979), this chapter includes all of the available firms in the airline and oil industries.

5. *Size.* Instead of using small firms within a target population, our sample consists of the largest firms in their industries. For example, the sampled firms in the banking industry are selected from the top 13 largest ones.

While attempting to resolve these limitations, we also make sure that the grouping results are not artifactual. As discussed in chapter 2, by minimizing within-group variance and maximizing between-group variance, the cluster algorithm by itself produces clusters regardless of whether there is structure in the data or not. Because the F test (or its kind) bases its tests on minimized within variance and maximized between variance, statistical significance tests based on the cluster/F test approach tend to make a Type I error. For this reason, many studies to date have falsely concluded that artifactual groupings are statistically significant. In an effort to overcome these artifactual and Type I error problems, in this chapter, the sample firms are deliberately chosen from obviously different groups, and the grouping results are referenced to their actual reality (face validity). In addition, we check the historical consistency of grouping structure over time. If the groups found are artifactual, it is very unlikely to observe historical consistency, especially considering that the stock returns are 'hard' data and no subjective manipulations have been made in grouping. In the following section, the sample and analytical method will be presented.

3.3 Method

3.3.1 Sample

41 firms are used for classification in this study. Among them, 12 firms are involved in banking, 20 firms are doing oil-related businesses, and 9 firms are in the airline industry (see Table 3.1).

The 12 sample firms in the banking industry are chosen based on assets from the top 13 firms listed in the 100 largest commercial banking companies (1993).[24] Although the SIC classifications differ at the 4-digit level (i.e., 6711, 6712, or 6025), the sample firms are regarded as competing in the same banking industry (Fortune, May 30 of 1994). In choosing the sample firms in the oil industry, all the firms in the oil refinery industry (SIC=2911) are included regardless of their size. Therefore, the sample firms share the same 4-digit level of SIC. In the airline industry, all the available firms in SIC=4511 or 4512 are included in the sample firms (We include the firms with 4512 because some firms like U A L are obviously competing mainly in the airline industry).

Among firms which meet the above criteria, the final 41 firms in the sample are screened out by their stock return data availability: the sample firms are listed in the NYAM (New York and American Stock Exchanges) and have complete stock returns over the sample period in the University of Chicago's Center for Research in Security Prices (CRSP) data tapes. Since our study employs 1-year, 2-year, 3-year, and 5-year sample

[24] See Fortune, May 30, 1994. The First Union Corporation ranked 9th is not included in the sample because of lack of stock return data.

windows, the 41 samples require complete stock returns over these periods. Any firms which do not have complete data are not included in this study.

Because the selection of samples should be free from any subjective judgment, we do not include or exclude any sample firms because of seemingly obvious misspecification of SIC-based classification. For example, Spelling Entertainment Group Inc. has the SIC of 2911 even though they are in the business of TV programs and feature films. Their sales in 1993 were only $599.8 million with 1,000 employees. Although their business and company size can not be compared with major oil companies like Exxon or Mobil, the firm is included in the oil sample firms since its SIC is the same. Another example is WorldCorp. Their business is not directly involved in the passenger airline transportation (despite their SIC of 4511). Their sales volume is just $204.4 million with 725 employees, while the smallest (Alaska Airline) firm in the airline industry has sales of $1,315.6 million with 8,458 employees. Although the differences are significant, WorldCorp is included with the passenger airline transportation. These "anomalies" provide interesting challenges to the stock return method.

3.3.2 Variables

For each company in the sample, a complete set of 250 weekly stock returns during the period of 1988 to 1992 are prepared for study. For raw data, weekly returns are used rather than daily returns because weekly returns neutralize erroneous shocks. By aggregating daily returns (see section 3.3.3.1), weekly returns correct any daily misinterpretations of disturbances, if any.

The variables used in the method are between-firm correlation coefficients of stock return residuals. The between-firm correlation coefficient captures magnitudes and directions of instantaneous stock return movements reflecting disturbances over the sample period. Since both the magnitudes and directions are meaningful in analyzing stock return movements, the correlation coefficient is chosen as variable measure over distance measure, such as Euclidean distance. In our sample, weekly stock return residuals (after eliminating systematic risk) are correlated between the sample firms each week over the chosen sample windows. For example, under the 3-year sample window period, the 150 weekly abnormal stock returns of two firms among the sample firms are correlated, and the between-firm correlation coefficient is used as a summarizing measure for comovement. In the same manner, 1-year, 2-year, and 5-year sample data are prepared with 50, 100, 250 weekly returns, respectively.

3.3.3 Analytical Method

Pursuant to our research objective, the following subsections present the analytical design. At the initial stage, the security returns residuals from all the sample firms are obtained and are correlated among firms in order to calculate summary statistics for comovement. Since we adopt 1-year, 2-year, 3-year, and 5-year sample windows in the study, the between-firm correlation coefficients are obtained for each chosen sample window. At the second stage, the summary statistics are analyzed so that firms which move similarly can be grouped together (clustering). At the final stage, the resulting groups are analyzed for their validity.

3.3.3.1 Eliminating Systematic Movements

The systematic movements related to changes in the market index are eliminated from total security returns. The value-weighted market index from the NYAM is used for the market measure of the market movement that is common to all securities traded on exchange. The separation of market portfolio variation is done using the market model:

$$r_{i,T} = a_i + b_i\, r_{M,T} + e_{i,T} \qquad (1)$$

where:

$r_{i,T}$ = weekly stock return for stock i on week T

or

$= (r_{i,t+1}+1) \times (r_{i,t+2}+1) \times ((r_{i,t+3}+1)) \times ((r_{i,t+4}+1)) \times ((r_{i,t+5}+1)+1) - 1,$

$t = 5(T-1)$, where $T = 1,2,3,\ldots,50$

$r_{i,t}$ = daily stock return adjusted for stock split and dividend payment for stock i on day t

or

$= \{ p^*_{i,t} - p^*_{i,t-1} + d_{i,t} \} / p^*_{i,t-1}$

$p^*_{i,t}$ = $p_{i,t} \times s_{i,t}$, $s_{i,t}$ = coefficient for stock split adjustment

$r_{M,T}$ = weekly return on market portfolio (value weighted) at week T

a_i, b_i = coefficients in the model for stock i

$p_{i,t}$ = the price of security i on day t

$d_{i,t}$ = the dividend, if any, paid on day t for security i

$e_{i,T}$ = disturbance in the model for security i at week T

- this is normally distributed with mean 0 and variance q^2_i

i.e., $e_{i,T} \sim N[0, q^2_i]$.

This regression model estimates an intercept term (a_i) and the comovement (b_i) of individual security returns with the movement of the market index. Any variation due to factors not presented in the market portfolio will be captured in the disturbance term $e_{i,T}$.

The residuals from the market model regression are traditionally interpreted as abnormal returns --- the securities returns in excess of expected returns, or

$$AR_{i,T} = r_{i,T} - \{ a_i + b_i r_{M,T} \} \qquad (2)$$

The residuals or weekly abnormal returns (WARs) reflect firm-specific variation including subgroup common variances, if any, and a noise term, and are 'free' of total market movement. When there exists significant niche perturbance resulting from mobility barriers, the residuals will reflect such group common variances or

$$AR_{i,T} = \alpha_{i,T} + \beta_{g,T} + \varepsilon_{i,T} \qquad (2)'$$

where:

$\alpha_{i,T}$ = firm-specific factor for firm i at time T

$\beta_{g,T}$ = group-specific factor for group g at time T

$\varepsilon_{i,T}$ = disturbance in the model for security i at time T

- this is normally distributed with mean 0 and variance q'^2_i

i.e., $\varepsilon_{i,T} \sim N[0, q'^2_i]$.

3.3.3.2 Resemblance Coefficient

The residuals from the market model are used to cluster groups in such a way that firms with similar directions and magnitudes of residual changes over the time span of sample data are grouped together. Specifically, the WARs of each firm from the regression analysis are correspondingly correlated with those of another firm, and the correlation coefficient matrix between firms is used for a measure of directions and magnitudes of residual changes. Thus, the between-firm correlation coefficient or r_{ij} is a statistic which summarizes the closeness of abnormal return movements between firm i and firm j over the chosen sample time span. For example, if the abnormal returns of firm i and firm j move in the same direction and magnitude over the sample windows, the between-firm correlation coefficient will be 1 (Note that the between-firm correlation coefficient ranges from -1 to 1). Because the directions and magnitudes of spontaneous changes in stock returns per week are the basis for clusters, the between-firm correlation coefficient is a more effective statistic than others such as the Euclidean distance measure. This measure captures absolute distance between residuals changes, but can not show their direction. In the stock return method, both direction and magnitude are considered.

The between-firm correlation coefficient is linearly transformed into a range of 0 to 2 without losing their ranking relationship. The linear transformation function is:

$$L(x) = -1 * (x - 1) \tag{3}$$

where, x = between-firm correlation coefficient (-1 =< x =< 1)

The r_{ij} of 1, which means perfectly correlated movements of WARs between firm i and firm j over the sample window, is transformed to 0; and the rij of -1, which means perfectly negatively correlated movements of WARs, is transformed to 2. Since this linear transformation is a one-to-one mapping, there is no information loss regarding the closeness of stock movements. The transformed between-firm correlation coefficient matrix becomes input distance data for cluster analysis.

3.3.3.3 Clustering Algorithm

The Ward's (1963) minimum variance method is used for classifying the sample firms into groups so that the stock returns of a group can comove significantly over the chosen sample window. Technically speaking, the method clusters those firms whose distances of transformed between-firm correlation coefficients are the closest into the same group. In the Ward method, the distance between two clusters is the ANOVA sum of squares between two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation. The Ward method is chosen because it outperforms in every respect, except the outlier problem of other algorithms, including the centroid method (Kuiper and Fisher, 1975; Blashfield, 1976; Mojena, 1977; Milligan, 1980).

3.3.3.4 Stopping Rules

Pseudo F statistic (Calinski and Harabasz, 1974) and Pseudo T^2 statistic (Duda and Hart, 1973) are used for determining the number of clusters[25]. Pseudo F statistic (Calinski and Harabasz, 1974) is computed as [trace $\mathbf{B}/(k-1)$]/[trace $\mathbf{W}/(n-k)$] where n and k represent the total number of samples and the number of clusters in the solution, respectively. The **B** and **W** terms are the between and pooled within cluster sum of squares and cross products matrices. Plainly speaking, Pseudo F is a sufficient statistic which can test a null hypothesis that k clusters are not statistically significantly different. Thus, the larger the value of Pseudo F statistic is, the better a group becomes separated into two.

[25] In an evaluation of 30 stopping rules which have appeared in the clustering literature, Milligan and Cooper (1985) conclude that the Calinski and Harabasz index (Pseudo F statistic) is the most effective,

Duda and Hart (1973) propose Pseudo T^2 statistic or $J_e(2)/J_e(1)$ where $J_e(2)$ is the sum of squared errors within a cluster when the data is partitioned into two clusters, and $J_e(1)$ is the squared errors when only one cluster is present. Therefore, smaller Pseudo T^2 statistic represents that two partitions explain better than one cluster. In determining the optimal number of clusters in our analysis, we look for the highest F value with largest marginal drop of T^2 value.

3.3.3.5 Principal component Analysis

In order to interpret the clusters found, we use the principal component analysis to summarize the data. As Rao (1964) maintains, the analysis is a valuable tool to derive a small number of linear combinations (principal components) of a set of variables that retain as much of the information in the original variables as possible. Principal components can be used to reduce the number of variables in regression and clustering. Plots of principal components can especially provide valuable insights on explanatory data analysis (Morrison, 1976). King (1966) uses the analysis to find that there exists *market component* and *industry component* in weekly stock returns. In order to check whether there are *industry component* and *subindustry component* in our particular sample data (note that we remove market component), and to show graphically how much principal components explain the group differences, we apply principal component analysis into our sample.

---

and the Duda and Hart statistic (Pseudo T^2 statistic) is the second most effective.

3.4 Results

3.4.1 The Number of Groups

Table 3.2 presents Pseudo F and Pseudo T^2 for a given number of groups derived by the clustering algorithm. Since the sampled firms are drawn from three distinct industries, it is expected that the optimal number of groups would be three. Each Pseudo F (Calinski and Harabasz, 1974) shows its 2nd highest peak at three clusters across the 4 windows (F_1=10.0, F_2=8.6, F_3=8.8, and F_5=9.0, respectively). At three clusters, the Pseudo T^2 statistic (Duda and Hart, 1973) shows the largest drop in all 4 cases (T^2_1=3.9, T^2_2=3.5, T^2_3=5.6, and T^2_5=4.2, respectively) and bounces back up around six clusters and then drops to around nine clusters.

Since we are interested in whether the method can distinguish 3 different industries, 3 clusters will be analyzed in this chapter. By allowing as many clusters as possible, we increase the chance that the 3 industries might collapse into meaningful subgroups. In order to analyze the subgroup structure by allowing many clusters, we will study 9 clusters. In the following section, the nature of the three and nine clusters are presented.

3.4.2 The Nature of the Clusters

Since the sampled companies are drawn from distinctive oil, banking, and airline industries, the groups found are referenced to their actual industries in order to check for face validity. Table 3.3 describes group memberships derived by the stock return method. As shown clearly, the firms in cluster 1 belong to the airline industry, and those in cluster 2 are in the banking industry, while those in cluster 3 are firms in the oil industry. In the 2-year window, some firms in the oil industry which are especially in the lower hierarchical level in the clustering tree are misfit into airline firms (i.e. Ashland Oil Inc., Diamond Shamrock Inc. and etc. in Table 3.3). Note that all the firms in the oil refinery industry (SIC=2911) are included in the sample although the nature of their business varies. Nonetheless, in the longer windows, the main grouping structure becomes more similar to reality. In the 3-year and 5-year windows, the classification of the firms in all industries becomes perfect and persistent (see groups in 150 weeks and 250 weeks of Table 3.3).

One misfit is the case of Worldcorp which has been clustered in cluster 3, the oil industry. As described in section 3.3.1, WorldCorp is considered an outlier in the airline industry because its business is not directly involved in the passenger airline transportation (despite their SIC of 4511). Its sales volume is just $204.4 million with 725 employees. Comparing the company in sales and number of employees to the smallest firm (Alaska Airline), whose sales is $1,315.6 million with 8,458 employees and to the second smallest one (Southwest Airline), whose sales is $2,592.0 million with 16,818 employees, WorldCorp should behave differently from the other airline firms.

Another misfit is the Spelling Entertainment Group Inc. who is in the business of TV programs and feature films. The company has oil industry SIC of 2911, and is classified into the lower hierarchical level in the oil industry (see Table 3.3, 3.4 and Exhibit 3.2). Group members include Howell Corp, WorldCorp Inc., Norsk Hydro A S, and Quaker State Corp. Considering Spelling's sales volume ($599.8 million in 1993) and the number of employees (1,000 employees), their business and company size can not be compared with major oil companies like Exxon or Mobil. Spelling should not be grouped with the major oil companies (see Table 3.4 and Exhibit 3.2). Nonetheless, Spelling's classification into the lower hierarchical level in the oil industry (see Table 3.3) is reasonable because the industry is most varied one among the three industries. Since our method forces all the sample firms to be classified into 3 clusters (Table 3.3), it is expected that any outliers, if any, whose variation is the highest would be grouped together, and their hierarchical level in the clustering tree should be lower. Note that all the firms in the oil refinery industry (SIC=2911) are included regardless of their size (see section 3.3.1).

Considering that the grouping results have been derived from 'hard' market returns without any subjective manipulations, the historically consistent and well-fitted results imply that the method works at the level of entire industries. Although it is originally designed to detect industry substructure in a micro context, the method may also be used for identifying industry structure in a macro context. Note that in chapter 2, subgroups are detected in one industry, while in this chapter (3), industry as well as subgroup memberships among firms across 3 industries are identified.

Table 3.4 shows industry subgroup specifications. The firms in clusters 1, 6, 7, 8, and 9 belong to the oil industry. Those in clusters 3 and 4 belong to the banking industry while those in clusters 2 and 5 are part of the airline industry. In the oil industry, market leaders like Chevron, Mobil, Exxon, Philips, Atlantic, Amerada, KERR, and Murphy are grouped into the same group (cluster 1) consistently over the 4 windows. The other non-market leaders are less consistent. Even though the samples are chosen from the same SIC of 2911, it appears that there are more diverse industry subgroups within the group. It also seems that the SIC-based classification does not produce the most homogeneous groupings. Considering that a primary role of taxonomic method is to provide homogeneous groups for high quality research (McKelvey, 1982), the SIC-based classification may not be the best method.

In the banking industry, all of the banks (cluster 3) except Banker's Trust, JP Morgan, and Banc One Group (cluster 4) group together consistently across the 5-year sample period. These banks are separate from other major nationwide retail-oriented banks in terms of their institutional banking emphasis. Unlike those in the oil industry, the sample firms are chosen from the top 13 largest banks. In our sample, their groups are very consistent over the 5-year span and are regarded as competing in the same industry by practitioners (Fortune, 1994). Their SICs are widely different (6025, 6711, and 6712) and are not highly correlated with the groupings.

In the airline industry, all the major firms such as American, U A L, Delta, and US Air are consistently classified together (Cluster 2), while British and KLM are grouped differently (cluster 5). WorldCorp behaves very differently from other airline firms. Considering that WorldCorp is an outlier, as mentioned in section 3.3.1, this is to be expected. Although all the sample firms including WorldCorp (except U A L) have the same SIC of 4511, British and KLM are obviously separated from other major US domestic airline firms. Despite its different SIC of 4512, U A L is consistently grouped with the other major firms.

There are some misspecifications in the groups. We find 4 misfits in the 1-year and 2-year windows, and 1 misfit afterwards. The most misfit firm in our sample is Worldcorp: across all of the 4 windows, it is never categorized into any of the airline groups even though it has an airline SIC code. The second most misfit is Spelling Entertainment Group which is not an oil-related firm, but has been somehow classified into the SIC of 2911 (see section 3.3.1). This firm has not behaved like other firms in the oil industry, and is categorized inconsistently.

3.4.3 The Nature of Factors

In order to interpret the structure in the data, principal component analysis has been applied across the 4 windows. Note that because the market component has been removed from total variations, principal components do not reflect systematic market effects. Table 3.5 shows the eigenvalues and their explanatory proportions for the most critical 5 principal components from possible 41 principal components. An interpretation of eigenvalues is the explained proportion of total variance, due to its linear combinations of the independent variables (principal component). As exhibited in Table 3.5, the impact of principal component 1 is significant: its explaining proportion is 40 percent, 33 percent, 35 percent, and 36 percent of total variations, respectively, across 4 windows. In our particular sample, the first principal component distinguishes between banking and oil industry as well as between airline and oil industry (see Exhibit 3.2).

The effects of the second principal component are also significant. Note that the explaining the proportion of PRIN2 is 13 percent, 16 percent, 15 percent, and 15 percent, respectively. Although the interpretation of the second principal component is not as clear in our particular sample, it distinguishes between banking and airline industry (see Exhibit 3.2).

Exhibit 3.2 shows 4 graphical plots of firms based upon their loadings on the 1st and 2nd most important principal components. Because those two principal components explain more than 50 percent of original data, their plot is an effective graphical presentation of information retained in the data. Each plot shows each sample firm's loading scores at a chosen window (say, 1-year window for the first one), and oil and banking firms are represented by 'z' and 'x', respectively. Airline firms are represented by the first character of their company name (say, 'A' for American Airline).

As shown clearly, the plots of each firm are stable with respect to industries over the sample windows. The banking firms ('x'), stay on the left-low corner of the plot plane, and the width of variations is tight (between -6 and -2 for PRIN1 and between -4 and 0 for PRIN2). The firms in the airline industry are located at the left-upper side. Their patch lies between -4 and 0 along PRIN1 and between 0 and 5 along PRIN2. On the other hand, the oil firms ('z') are scattered over the right-middle area, and their variation width is larger along the 1st principal or PRIN1. Nonetheless, the firms in the lower right corner are stable over all time spans (see CL1 in Table 3.4 for their names). Along with *stability*, an inference is that the substructure of the oil industry is more complicated, yet the substructure of the leader group (i.e. CL1 in Table 3.4) is clearly distinguishable from other groups in the banking and airline industries.

It can also be observed that the longer the time span is (up to 5 years at least), the tighter and clearer the classification is. Comparing the 1-year and 5-year windows, the plot of the 5-year window is much tighter; for example, the variation width of banks is much narrower. For the years chosen, the 5 year window did not stretch into a period of evolutionary instability even for the airlines. Empirically, the choice of optimal sample periods can be important. Too short a sample span may not capture a sufficient number of outside disturbances which are source of covariance grouping. Too long a span may include evolutionary structural changes in their snapshot-classification, resulting in a mixture of responses to structural changes and spot-responses to disturbances. In our particular data, the 3-year window seems to be an optimal choice as a sample period. It can be inferred that there has not been significant evolutionary structural changes among those industries because grouping structure stays consistent both in the 3-year and 5-year windows (1988-1992 time frame).

3.5 Discussion and Conclusion

In order to further develop the stock return method, this chapter discusses the issues of face validity, sampling window, and potential substitution of SIC-based grouping. Although statistically significantly different, the groups found in chapter 2 fail to provide a clear face validity. In this chapter, we carefully chose 41 sample firms from the oil, banking, and airline industries because these industries are obviously distinct and heavily specialized to one industry (nonaggregated). Because the stock return method is based upon group-common variations, its extension to industry-common variations appears conceptually natural. Empirically this extension may be important because it can provide face validity. Furthermore, the currently popular, yet problematic classification based on SIC code can be replaced by, or at least referenced to, the proposed method's classification.

A one-year sample window may be too short of a time to reflect fully the significant niche disturbances, and no empirical evidence to date has been documented with respect to how the choice of sample window affects optimal groupings. Empirically, too short a sample span may not capture a sufficient number of outside disturbances which are the basis of grouping. Too long a span may include evolutionary structural changes in their snapshot-classification, and stock return data may reflect both structural-responses to evolutionary changes and spot-responses to disturbances. In this chapter, the sample period window is extended from the previous one year window to 4 different windows, namely 1-year, 2-year, 3-year, and 5-year window spans. The grouping results from the different windows have been analyzed in order to evaluate the effectiveness of the stock return method.

To study these issues, the weekly abnormal returns of the 41 sample firms, listed on NYAM, are obtained over 1-year, 2-year, 3-year, and 5-year windows through a market regression model. Then, using product-moment resemblance coefficients, Ward's algorithm for clustering, and analytical stopping rules, we discover subgroups over the various windows. Principal component analysis is then used to interpret data structure and clusters found.

We find that the stock return method produces stable group classifications across different sample time spans. In our particular sample, the groups found show a clear face validity, and as the time span increases from 1 year to 5 years, the group structures become clearer and tighter. The stability of groups found has been longitudinally maintained along those periods. We also find that the method can detect stable industry-level effects, and that such distinctive industry structure extends over the several sample periods. Although the method is designed to find substructural patterns in a micro level, it seems possible to use it for detecting industry differences in a macro level.

While considering the results of grouping have been derived from objective 'hard' market returns over 5 year time span, the consistencies of structural grouping from the stock return method apparently imply that the stock return data bears the information of variance on critical attributes of firms and niches including industries. That is, stock returns seem to reflect variance on *any* reasonably relevant attribute, as long as there is change in the attribute that is noticed by security observers.

Finally, we can draw several conclusions from this study. First, the stock return method can effectively identify industry subgroups as maintained in chapter 2. The findings show that the groups found provide clear face validity (Table 3.3, 3.4 and Exhibit 3.2). The evidences confirm that industry substructure can be reliably and validly separated, and that substructure stability has been longitudinally maintained across different sampling times of stock returns. Although it is originally designed to detect industry substructure in a micro context, the method may be used for identifying industry structure in a macro context. Second, the identified group structure is not artifactual. The historically consistent results from our method using 'hard' market-equilibrium data render a high level of validity on our finding. Our finding clearly moves onto higher ground relative to the many prior studies reviewed by McGee and Thomas (1986). Third, the findings are objective because the sample data used are 'hard' data, and the stock return method has no subjective decisions buried within it (including clustering methods). Finally, this method uses one data source which is easy to access and less costly to acquire.

In our sample firms, the stock return method worked under both micro and macro levels. The three industry groups found obviously reflect their own industries, and the subgroups found are stable and meaningful. Besides objective and replicable results, there are many other advantages to the stock return method, including: the data are readily available and easily accessible; data collection problems, and arbitrary or subjective choices can be avoided; the stock returns reflect broad tendencies in firm and niche attributes; longitudinal studies are easily feasible, and so forth.

Although several significant limitations of chapter 2 are resolved in this chapter (3), there still remain some limitations:

1. *Effect of industry dynamics.* Once the longitudinal structural changes within an industry are analyzed, and the stable structural time periods are found (SSTPs), then analysis of strategically similar groups becomes much more meaningful (Fiegenbaum and Thomas, 1990: 198). This chapter is limited to a static analysis without investigating longitudinal changes and SSTPs.

2. *No* R *statistic.* We would have strongly preferred to use Johnson's (1994) method, based on

Friedman and Rafsky's R, but stock returns call for the product-moment resemblance coefficient and the R coefficient has only been tested for difference coefficients. Our use of the historically-observed consistencies of results is a somewhat oblique approach to testing for statistical significance.

3. *Local optima.* Clustering methods run the risk of producing locally optimized clusters rather than globally optimized ones. Since no clustering package available to us uses a randomized initialization procedure, we can not avoid the local optimization possibility. This could lead to more overlap among the groups than is actually true for the data.

While recognizing limitations, we believe that further development of the stock return method will be meaningful and rewarding. There are at least three possible avenues for future research. First is to develop theories which best explain the causes for structural differentiation among firms. That is, what aspects of firm behavior are dependent on, or determine industry structure? Is industry structure largely a function of niche attributes or firm attributes? Or, are the two inseparable? Second is to examine the effects of structural differentiation among firms: the relationship between groups and groups' performance levels, as well as among group members and their individual performance levels. A recognized difficulty in pursuing these issues has been finding a firm-specific risk-adjusted profitability measure; to date, the standard deviation of return on sales or return on assets has been used to measure risk (Cool and Schendel, 1988; Cool, Dierickx, and Jemison, 1989). Elimination of market-evaluated financial risk from profitability could provide better insights into these issues. Third is to develop a clustering method. There are a variety of cluster method technicalities that need further research in the applied setting of organizations. Which resemblance coefficients should be used? Which cluster algorithms should be used? What statistical approach should be taken? What kinds of non-stock return characters should be used to test the validity of the stock return groupings? What other methods of assuring face validity of the clusters are possible?

Although primitive, this study promises the possibility of the stock return method as an alternative classification method to the SIC based methods. Although the SIC code has been the main approach to grouping firms, as noticed in this chapter, a blind use of the SIC code may cause misleading results. If this method can provide better groupings than the SIC code, it would generally boost the quality of research on strategy and intra-industry studies because homogeneous grouping is critical to high quality results (McKelvey, 1982).

Chapter 4

On the Dynamic Stock Return Method to Analyzing Longitudinal Airline Industry Substructure

4.1 Introduction

The potential importance of strategic group analysis as an analytical construct for theory-building has long been recognized, and several empirical methods which analyze longitudinal structural dynamics in an industry have been proposed in the field (Caves and Porter, 1977; Hatten and Hatten, 1987; Cool and Schendel, 1987, 1988; Fiegenbaum, Sudharshan, and Thomas, 1987; Fiegenbaum and Thomas, 1990; Bogner, Mahoney, and Thomas, 1993; Cho and McKelvey, 1996). Cool's (1985) attempt to identify structural changes over time in the pharmaceutical industry has been followed by many others who have further developed these methods (For example, Cool and Schendel (1987), Fiegenbaum, Sudharshan, and Thomas (1987), and Fiegenbaum and Thomas (1990)). Their methods are based on specifying crucial strategic dimensions at a certain point of time, and based on the chosen variables along the strategic dimensions at that time, the longitudinal structural changes are analyzed.

As insightful as their methods are, these methods suffer from some limitations including the arbitrary and subjective choices of critical strategic dimensions and variables which may not induce objective and replicable groupings. Although in previous chapters, the arbitrary choice of variables has been justified through strong results of F-tests, the results are questionable since we know that the F-tests are statistical artifacts (Barney and Hoskisson, 1990; Johnson, 1995; Cho and McKelvey, 1996). Because clustering methods themselves produce groups so that the between-variance is statistically larger than within-variance, the statistical significance between groups using variants of the F-tests cannot assure that in fact there are groups in a data. In addition, it is implicitly assumed that the chosen strategic dimensions are critical all the time. But, it is more likely that the characteristics of the competitive environment change over time, and the chosen strategic variables at one time may not be as critical in subsequent time periods. Furthermore, a fragmental choice of some strategies does not necessarily span a firm's structure (Diericks and Cool, 1989), resulting in possibly incomplete and misleading outcomes.

In this chapter, the stock return method is further developed to analyze longitudinal structural dynamics. There are two motivations for this chapter. First is to fulfill the need to develop an objective and replicable method of analyzing longitudinal changes in an industry substructure. Partly because it determines subgroups based on the more objective market-driven stock returns rather than on arbitrary strategic variables, and partly because critical factors determining subgroups are identified by efficient capital market, the stock return method can produce objective grouping solution over multiple time periods. Second is to enhance the validity of the stock return method by applying this method over a longer time period. If this method can identify reliably and validly separated industry substructure over a short time period (i.e. 1 year time span), the stock return method should also be able to produce longitudinally stable groups over a longer period (i.e. 15 year time span). Since the groups are derived *consistently* across different time spans without the researcher's subjective choice of methods or variables, results which confirm the industry's historical progress (based on actual facts) over a long time span will ensure a high level of validity for using the stock return method.

In this study, we apply the stock return method to the airline industry over the period from 1979 to 1992 in order to detect longitudinal changes in its substructure from the industry's deregulation in 1978. In our particular sample, the results confirm the industry's historical progress and the stability of results along the long-term period. Although not perfectly related to the longitudinal dynamics of groups, accounting data such as market share or productivity support our findings. From the longitudinal analysis of relative closeness, the leading firms like American, United, Delta, and Northwest show the highest grand correlation coefficients, meaning that their stock movements are very close together over a longer time period. On the other hand, the stock returns of niche-specific firms like Hawaiian and Aloha have moved closely together among themselves, but their stock returns have not moved closely with the leading firms. These findings suggest that the stock return method is an effective method to identifying industry substructure even over a longer time span.

The remaining sections are presented as follows: Section 4.2 reviews theoretical and empirical background. Section 4.3 describes the sample data and outlines the method. Results are discussed in section 4.4. Discussions and conclusions are presented in section 4.5.

4.2 Theoretical Background

Since 1985, many empirical methods have been developed in identifying industry subgroups over multiple stable strategic time periods (SSTPs)[26] (Cool; 1985, Cool and Schendel; 1987, Fiegenbaum, Sudharshan, and Thomas; 1987, and Fiegenbaum and Thomas; 1990). In identifying subgroups, the following five steps have been taken utilizing the characteristics of the competitive environment or *strategic space* [27] as the source for grouping.

The first step concerns the choice of the overall time period for the research study. The time period is normally determined based upon the selection of the industry and the purpose of the study. Step 2 involves the researcher's decision to examine corporate-, business-, or functional-level strategies and to assess which dimensions (components) best describe those strategies. (Cool and Schendel's argument that scope and resource deployment decisions reflect major strategic decisions has generally been followed). The third step involves identifying the variables which best capture the firm's scope and resource deployment decisions in the competitive context under study. Step 4 involves analyzing the stability of the variance-covariance matrix of the strategic variables in adjacent time periods and identifying SSTPs based upon the variables chosen in step 3. (The rationale is that when firms alter their commitments among the strategic variables, the covariance between these variables should reflect this strategic repositioning). In the final

---

[26] SSTP is defined as time periods of homogeneity with regard to competitive strategic behavior.

[27] Three dimensions, namely, the *levels* of organizational strategy (e.g. corporate, business and functional), the *components* of strategic dimensions (e.g. scope, resource deployment, etc. (Hofer and Schendel, 1978)), and the *time period* define the broad characteristics of the strategic space (Fiegenbaum and

step 5, firms are clustered into groups once SSTPs have been identified.

Although these identified methods are insightful, there are some key limitations. First, as mentioned in section 4.1, the likelihood of providing objective and replicable grouping is questionable with the arbitrary selection method of determining critical strategic variables. In previous chapters, the arbitrary choice of variables are justified because of strong results from F-tests. However, we know that the F-tests are statistical artifacts (Barney and Hoskisson, 1990; Johnson, 1995; Cho and McKelvey, 1996): the clustering methods themselves produce groups so that the between-variance is statistically larger than within-variance in terms of the arbitrarily chosen variables, thus weakening the support for the strong results from the F-tests.

The second limitation is the failure to incorporate longitudinal shifts in essential sources of competitive advantages. The longitudinal structural changes (i.e. at time $t+\Delta$) are analyzed assuming that the chosen variables at time t continuously play the most critical roles over the subsequent time periods. However, it is more likely that the characteristics of the competitive environment or *strategic space* change over time, and the chosen strategic variables at time t may not be as critical in subsequent time periods. Furthermore, a fragmental choice of some strategies do not necessarily span a firm's structure (Diericks and Cool, 1989), resulting in possibly incomplete and misleading outcomes.

In the stock return method, these limitations can be overcome, producing objective and replicable results. Because the critical factors determining industry substructure (i.e. harvesting capabilities and resource pool) are defined and reflected in the movements of

---

Thomas, 1990: 197).

market-driven security returns, this method can detect market-equilibrium critical factors. Thus, if there are longitudinal shifts in critical factors, these effects will be reflected in the stock returns through efficient capital market mechanisms. Furthermore, subgroups are not based on arbitrary strategic variables. As chapter 2 and 3 suggest, in the static context, industry subgroups found by the method have clear face validity and are statistically significantly different in terms of exogenous variables. Since the dynamic stock return method is based upon the static approach, we will discuss the static method briefly.

4.2.1 The Static Approach

The theoretical basis of the stock return method is niche perturbation hypothesis (Cho and McKelvey, 1996). In this framework, industry substructure is determined by characteristics of the resource pool[28] commensurate with the niche[29] as well as competitors of resource in the pool. Given the resource pool and competitors in place in a niche, firms who possess essential competencies (harvesting capabilities that are crucial to its survival

[28]In population ecology, environmental resources are generally defined as revenues, i.e., cash or kind, available in a niche, and they can be harvested by organizations depending upon their harvesting capabilities and competition structure within niche.

[29] Niche is defined as follows (Mosakowski and McKelvey ,1996): First, a niche is the "sum total of the adaptations of an organic unit" (Pianka, 1978: 238). A niche not only includes part of an organization's environment, but is also defined in part by the competencies the organization has available for harvesting the niche. Second, an occupying organization seldom, if ever, captures the full resource potential of a niche (because of incapabilities or competitors) (Hutchinson, 1957), meaning that further refining of its competency for harvesting is always possible. Third, it follows from this that while elements of an organization's niche are subject to manipulation as it develops relevant competencies, aspects of the broader environment, for all practical purpose, are not (McKelvey, 1982: 109). Fourth, the resource pool of a niche---generally defined as revenue both available and within an entity's competence for harvesting---is subject to change by events other than the behavior of its inhabitants, such as changing economic, technological, political and social elements. Fifth, resource pools co-evolve with the emergence of organizational forms suited for harvesting the resource. Finally, each niche contains other competitors who have also evolved along with the target firm and are able to compete more or less effectively for the

within a niche) can only draw revenues competitively from market against competitors (Aldrich, 1979; McKelvey, 1982, 1994; Hannan and Freeman, 1989; Mosakowski and McKelvey, 1996). Then, in equilibrium[30], efficiently surviving firms in a niche will have similar survival capabilities (competition groups) and any perturbations from inside and outside niche will similarly affect the harvesting potential and capabilities of firms in the group.

The key assumption in the stock return method is the efficient market hypothesis---observed security prices reflect "fully, correctly, and instantaneously" all the publicly available information (Fama, 1976; LeRoy, 1989; Fama and French, 1992). Any external niche shocks and resultant internal competitive impacts among niche resident firms will be "efficiently" reflected in their security prices via fierce market competition for arbitrage profit. Under this hypothesis, stock prices, and therefore stock returns[31] are accurate reflections of all available relevant information in the sense that self-interested rational arbitrageurs, recognizing that prices are out of equilibrium line, make a profit by buying or selling stocks, thereby driving prices back to equilibrium values consistent with available information (Ross, 1987; Huang and Litzenberger, 1988; LeRoy, 1989). Therefore, a change of stock returns of firms competing in a particular niche reflects a reequilibration of

---

resources.

[30] The crucial assumption is the fundamental interdependency between the nature of firms and the nature of niche resources available for harvesting (McKelvey, 1982; Nelson, 1994; Cho and McKelvey, 1996).

[31] We follow standard finance research practice in using "stock returns" rather than stock prices. Stock returns are derived from stock prices by taking into account dividend payments and stock splits (see Section 4.3.3.1 for detail).

the capital market's valuation of the underlying assets of firms in the niche[32]. Furthermore, changes in security returns due to a niche perturbation represent a market equilibrium valuation on the impact on the underlying firm (Lucas, 1978; Huang and Litzenberger, 1988).

The stock return method presumes that any niche perturbation will cause a spot-response in the stock returns (spot rates) of the resident competition group. Any actual or generally perceived or expected perturbation to the resource gradient (e. g. political, economic, environmental, technological, market, etc.) or niche competitor changes (e.g. a competing firm fails, or gains increased market share) will affect the harvesting potential and capabilities of firms in the group, and thus the value of firms in the resident competition group will change accordingly. Then, under the efficient market hypothesis, the change in the value of firms resulting from niche perturbations will be reflected concurrently in their stock returns. Therefore, if there exist industry- or group- common variations derived from niche disturbances, such common variations may induce different spot-responses in stock returns (spot rates) across industries or groups within an industry. In order to capture industry- and group-common variations, systematic (market) variance is eliminated from the total variance. Once the systematic risk is removed, the variance of residuals may represent individual risk as well as industry and/or group membership risk. Residual variations after eliminating market variation from total variation are as follows (see equation (2) and (2') in section 4.3.3.1):

---

[32] An interesting point made by Jaewoo lee is that the stock return method may not require a very stringent standard of market efficiency. Thus we do not need to be assured of instant reequilibration, only that attempts in this direction, in response to niche perturbations, produce niche related common variance.

Residual Variations = Total Variations - Market Variations, or

= Industry Variation + Group Variations + Error Term

By definition, the error term is random. If residuals of stock returns show significant common variations over time, we can infer that variations from industry- and/or group-common disturbances do exist. Without industry- and/or group-common variations, by definition, residual variations should be random, and common variations should not be identifiable systematically and persistently over time.

Although it appears that the stock return method uses a performance measure (stock return) as a clustering character, this is not really the case. The stock return method is concerned with group-level common variance resulting from niche perturbation, not the performance of individual firms. Group-level common instantaneous response of stock returns does not reflect individual firm's performance, but rather the niche perturbance. In an efficient capital market, the stock return response of group members will be instantaneously similar, given a niche disturbance, but their longer term performance will not be necessarily similar. The performance measures are not used to detect clusters—only to show common variance in group returns.

In addition, assuming that an incremental change in stock price is a market equilibrium valuation of the impact of disturbances on the underlying firm (efficient market hypothesis), theoretically speaking, the fact that there exist common stock return comovements guarantees that there have been a *sufficient* number of group-common shocks in the environment, and that those shocks have been *significant*. Therefore, the stock return method does not require checking, *a priori*, whether there have been significant numbers in group-common shocks and corresponding impacts.

4.2.2 The Dynamic Approach

The dynamic stock return method proposes that the persistent structural differentiation among firms over multiple stable structural time periods[33] induces different spot-responses on stock returns (spot rates) over time. As shown in Exhibit 4.1, because of the fundamental interdependency between the nature of firms and the nature of niche resources available for harvesting, each changes as the other changes (McKelvey, 1982; Nelson, 1994; Cho and McKelvey, 1996). If there are substantial changes in their niche and/ or niche competitors (significant shift of SSTP), the essential competencies crucial to survival may change accordingly. Firms will survive if they are successful in respecifying their harvesting capabilities against competitors. Others will die out (Aldrich, 1979; McKelvey, 1982, 1994; Hannan and Freeman, 1989; Mosakowski and McKelvey, 1996). Then, in equilibrium, efficiently surviving firms in the new niche, say at time t+1, will have similar survival capabilities[34], and their survival capabilities will be different from those in the previous niche, say at time t. Exhibit 4.1 represents longitudinal changes in niche and niche competitors across different time horizons.

If so, under the efficient market hypothesis, the effects from niche perturbations on the stock returns of firms in a competition group will be similar as long as the niche attributes are stable (SSTPs). The stock returns of firms that are competing in a different SSTP, say time t+1, may respond differently from those in other SSTPs, say time t;

---

[33] Since our framework concerns with niche-specific structural characteristics, the term of stable *structural* time period is used instead of stable *strategic* time period

[34] See Cho and McKelvey (1996) for detailed discussion on the concept of resource partitioning, niche separation, and coevolutionary niche theory.

however, the stock returns of firms in a competition group will be similar within the same SSTP. Then, the niche-specific effects across different SSTPs can be isolated from the variation of stock return residuals by eliminating systematic and industry variation. This common niche-specific variation is the source for identifying longitudinal change of groups within an industry.

In addition to the method's objectivity, there are other advantages as follows: First, stock return data are readily available and easily accessible. Second, this method does not require operationalization of hard-to-quantify concepts such as assets and skills which determine structural differences. Third, since stock return data are well documented over time, it is feasible to do a longitudinal analysis. Fourth, measurement error problems associated with accounting data are resolved[35].

The major limitation of the method is that firms diversified across industries would not be appropriate for clustering. If a firm is involved in multiple businesses across industries, the effect from outside niche disturbances will be an aggregated one, and will obscure the effect a specific group perturbance has on individual SBU of interest. In order to empirically identify industry subgroups, nonaggregate group common effects should be identified, not aggregate effects. However, many important industries are basically composed of single-industry firms. For example, steel, oil, aluminum, public utilities, airlines, office equipment, and banking industries are composed primarily (but not exclusively) of firms heavily committed to that one industry (Ryan and Wittink, 1985).

---

[35] Fisher and McGowan (1983) argue that accounting information may not be consistent from firm to firm or group to group, and that accounting rates of return, even if properly and consistently measured, provide almost no information about economic performance.

Based upon the findings in chapter 2 and 3, and our motivation to improve objectivity and replicability in longitudinal analysis, the dynamic stock return method has been applied to the airline industry over the period from 1979 to 1992. Chapter 4 detects the resulting longitudinal changes in the airline industry substructure from the industry's deregulation in 1978. To check the stock return method's validity, the locus of identified industry substructure over time is referenced to the industry's historical evolution process. The group dynamics found are further referenced to the accounting data such as revenue, net income, and productivity. Finally, relative movement of a couple of designated firms to other competing firms are analyzed over the period from 1979-1992.

While developing the method in the dynamic context, we also make sure that the grouping results are not artifactual. As discussed in our previous chapters, by minimizing within-group variance and maximizing between-group variance, the cluster algorithm by itself produces clusters regardless of whether there is structure in the data or not. Because all variants of F test base their tests on minimized within variance and maximized between variance, statistical significance tests based on the cluster/F test approach have made a Type I error. For this reason, many researchers to date have falsely concluded that artifactual groupings are statistically significant. In an effort to overcome these artifactual and Type I error problems, in this chapter, the airline industry is deliberately chosen for its relative familiarity to the average reader (unlike electronics firms in chapter 2), and the grouping results are referenced to their actual reality (face validity). In addition, we check the historical consistency of grouping structure over time. If the groups found are artifactual, it is very unlikely to observe historical consistency, especially considering that the stock returns are 'hard' data and no subjective manipulations have been made in grouping. In the following section, the sample and analytical method are presented.

4.3 Method

4.3.1 Sample: Airline Industry

30 firms in the airline industry are used for classification in this study (See Table 4.1). The sample firms represent all the firms with SIC designation of 4511 or 4512 during the period between 1979 to 1992. The 30 firms are highly specialized in the airline business partly because of legal constraints. The sample firms are listed in the New York or American Stock Exchanges and have complete stock returns of one year or 50 weeks over the sample period from 1979 to 1992 in the University of Chicago's Center for Research in Security Prices (CRSP) data tapes. The sample period of this study includes 171-month periods (1979- 1992) after the signing of the Airline Deregulation Act in October 1978 when business environment became increasingly less regulated.

With gradual deregulation of the domestic US air transportation beginning in 1978, and the reduced involvement of the Civil Aeronautics Board in the industry, airlines adopted quite different growth strategies and adjusted their structures according to the new environment. Thus, we expect to observe industrywide structural changes due to environmental changes in the years following the deregulation decision. For example, United Airlines extended its route structure to nationwide resulting in significant changes in its route structure by mid-1979 (Business Week, 1980). In 1978, Alaska Airlines served only 10 Alaskan cities and Seattle, but shortly after the Deregulation, Alaska extended operations into California.

The first half of 1980s can be described as a period of dense competition. Firms in the industry explore various possibilities for survival in face of fierce competition and uncertainty. While new firms entered into the industry seeking for niches (i.e.

geographical), existing firms (incumbents) tried to outperform though creative services and products. However, the successfully invented services and products were easily replicated by major competitors. An example may be the frequent fliers' mileage program launched first by American Airlines in 1981. In the same year, United counters with its own program, followed by TWA, Delta, Northwest, and Continental. During the second half of the 1980s, there were a significant number of mergers and acquisitions in the airline industry. In 1986, the acquisition activities were especially significant (see Table 4.5 or section 4.4.1). It can be referred as a period of consolidation (k-type) from diversified variation (r-type) during the first half of 1980s.

The industry has a history of unusually wide variability of the individual firms (Fruhan, 1972), and this wide variability continues to this date. This may suggest great heterogeneity in terms of market environment and business strategies, and perhaps the presence of several quite different strategic groups or niches within the industry. In many ways, the substructure of the airline industry is difficult to discern. There are no obvious industry subgroups other than the dichotomy between the large trunk airlines and the smaller regional airlines to which analysts sometimes refer (Forbes, 1981). Different geographic markets are growing at quite different rates, and all companies tend to have strength in only a limited number of geographic markets. No two airlines have strength in identical geographic segments. Thus, uncovering industry substructure in the air transportation industry is likely to be a challenging task. Considering these difficulties, if it works well here, the method may also work in other industries.

4.3.2 Variables

For each company in the sample, a complete set of 50, 100, 150, 250 weekly stock returns in the sample period from 1979 to 1992 are prepared for study. For raw data, weekly returns are used rather than daily returns because weekly returns neutralize erroneous shocks. The variables used in the method are between-firm correlation coefficients of stock return residuals. Specifically, weekly stock return residuals (after eliminating systematic and industry risk) are correlated between the sample firms each week in each year. The variables capture magnitudes and directions of instantaneous stock return movements reflecting disturbances over each sample year.

4.3.3 Analytical Method

In the following subsection, the analytical design of this chapter is detailed. The first phase is to obtain group identification via the stock return method. Residuals from security returns are obtained using market model across different time windows and then are manipulated so that meaningful dissimilarity matrices over time can be obtained. Summary statistics for comovement between-firm correlation coefficient are calculated by correlating residuals among firms. Then, firms are clustered via Ward's clustering method and stopping rules. The second phase is to check the resulting groups' validity by referencing the results to the industry's historical progress and accounting data. Furthermore, the longitudinal movement of other firms are examined relative to a couple of designated firms in the industry over the time period of 1979 through 1992. Since American Airlines and Alaska Airlines are distinguishable from the stand point of face validity, these two cases will be examined. A grand summary statistic is developed which summarizes stock movements between a firm and a designated firm (i.e. American) over the period of 1979 through 1992 or 15 years. A grand summary statistic is an average of coefficients measuring closeness of stock return movements over 50 weeks or one year.

Identifying Subgroups

4.3.3.1 Eliminating Systematic Movements

The systematic movements related to changes in the market index are eliminated from total security returns. The value-weighted market index from the NYAM is used for the market measure of the market movement that is common to all securities traded on exchange. The separation of market portfolio variation is done using the market model:

$$r_{i,T} = a_i + b_i\, r_{M,T} + e_{i,T} \tag{1}$$

where:

$r_{i,T}$ = weekly stock return for stock i on week T

or

$= (r_{i,t+1}+1) \times (r_{i,t+2}+1) \times ((r_{i,t+3}+1)) \times ((r_{i,t+4}+1)) \times ((r_{i,t+5}+1)+1) - 1,$

$t = 5(T-1)$, where $T = 1,2,3,...,50$

$r_{i,t}$ = daily stock return adjusted for stock split and dividend payment for stock i on day t

or

$= \{ p^*_{i,t} - p^*_{i,t-1} + d_{i,t} \} / p^*_{i,t-1}$

$p^*_{i,t}$ = $p_{i,t} \times s_{i,t}$, $s_{i,t}$ = coefficient for stock split adjustment

$r_{M,T}$ = weekly return on market portfolio (value weighted) at week T

a_i, b_i = coefficients in the model for stock i

$p_{i,t}$ = the price of security i on day t

$d_{i,t}$ = the dividend, if any, paid on day t for security i

$e_{i,T}$ = disturbance in the model for security i at week T

- this is normally distributed with mean 0 and variance q^2_i

i.e., $e_{i,T} \sim N[0, q^2_i]$.

This regression model estimates an intercept term (a_i) and the comovement (b_i) of individual security returns with the movement of the market index. Any variation due to factors not presented in the market portfolio will be captured in the disturbance term $e_{i,T}$.

The residuals from the market model regression are traditionally interpreted as abnormal returns --- the securities returns in excess of expected returns, or

$$AR_{i,T} = r_{i,T} - \{ a_i + b_i r_{M,T} \} \qquad (2)$$

The residuals or weekly abnormal returns (WARs) reflect firm-specific variation including subgroup common variances, if any, and a noise term, and are 'free' of total market movement. When there exists significant niche perturbance resulting from mobility barriers, the residuals will reflect such group common variances or

$$AR_{i,T} = \alpha_{i,T} + \beta_{g,T} + \varepsilon_{i,T} \qquad (2)'$$

where:

$\alpha_{i,T}$ = firm-specific factor for firm i at time T

$\beta_{g,T}$ = group-specific factor for group g at time T

$\varepsilon_{i,T}$ = disturbance in the model for security i at time T

- this is normally distributed with mean 0 and variance q'^2_i

i.e., $\varepsilon_{i,T} \sim N[0, q'^2_i]$.

4.3.3.2 Resemblance Coefficient

The residuals from the market model are used to cluster groups in such a way that firms with similar directions and magnitudes of residual changes over the time span of sample data are grouped together. Specifically, the WARs of each firm from the regression analysis are correspondingly correlated with those of another firm, and the correlation coefficient matrix between firms is used for a measure of directions and magnitudes of residual changes. Thus, the between-firm correlation coefficient or r_{ij} is a statistic which summarizes the closeness of abnormal return movements between firm i and firm j over the chosen sample time span. For example, if the abnormal returns of firm i and firm j move in the same direction and magnitude over the sample windows, the between-firm correlation coefficient will be 1 (Note that the between-firm correlation coefficient ranges from -1 to 1). Because the directions and magnitudes of spontaneous changes in stock returns per week are the basis for clusters, the between-firm correlation coefficient is a more effective statistic than others such as the Euclidean distance measure. This measure captures absolute distance between residuals changes, but cannot show their direction. In the stock return method, both direction and magnitude are considered.

The between-firm correlation coefficient is linearly transformed into a range of 0 to 2 without losing their ranking relationship. The linear transformation function is:

$$L(x) = -1 * (x - 1) \qquad (3)$$

where, x = between-firm correlation coefficient (-1 =< x =< 1)

The r_{ij} of 1, which means perfectly correlated movements of WARs between firm i and firm j over the sample window, is transformed to 0; and the r_{ij} of -1, which means perfectly negatively correlated movements of WARs, is transformed to 2. Since this linear transformation is a one-to-one mapping, there is no information loss regarding the closeness of stock movements. The transformed between-firm correlation coefficient matrix becomes input distance data for cluster analysis.

4.3.3.3 Clustering Algorithm

The Ward's (1963) minimum variance method is used for classifying the sample firms into the groups so that the stock returns of a group comove significantly over the chosen sample window (say, 1-year, 2-year, 3-year, and 5-year windows). Technically speaking, the method clusters the firms whose distances of transformed between-firm correlation coefficients are closer to the same group. In the Ward method, the distance between two clusters is the ANOVA sum of squares between two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation. The Ward method is chosen because it outperforms other algorithms in every respect, except for the outlier problem, including the centroid method (Kuiper and Fisher, 1975; Blashfield, 1976; Mojena, 1977; Milligan, 1980).

4.3.3.4 Stopping Rules

Pseudo F statistic (Calinski and Harabasz, 1974) and Pseudo T^2 statistic (Duda and

Hart, 1973) are used for determining the number of clusters[36]. Pseudo F statistic (Calinski and Harabasz, 1974) is computed as [trace $\mathbf{B}/(k\text{-}1)$]/[trace $\mathbf{W}/(n\text{-}k)$] where n and k are the total number of samples and the number of clusters in the solution, respectively. The **B** and **W** terms are the between and pooled within cluster sum of squares and cross products matrices. Plainly speaking, Pseudo F is a sufficient statistic which can test a null hypothesis that k clusters are not statistically nor significantly different. Duda and Hart (1973) propose Pseudo T^2 statistic or $J_e(2)/J_e(1)$ where $J_e(2)$ is the sum of squared errors within cluster when the data is partitioned into two clusters, and $J_e(1)$ is the squared errors when only one cluster is present. Therefore, smaller Pseudo T^2 statistic represents that two partitions explain better than one cluster.

Analysis for Validity

4.3.3.5 Referencing to the Industry's Historical Progress

Once groupings are obtained across different sample windows over the period of 1979 to 1992, they are investigated whether substructure dynamics found make sense from the perspective of actual industry progress. In order to observe incremental structural changes, groups under 50 week window are compared with those under 100, 150, and 250 week windows sharing the same base year (Table 4.2). Since 1986 is the beginning of mergers and acquisitions in the industry after the deregulation in 1978, the base years are selected accordingly. In addition, groups under the 150 week window are further prepared

[36] In an evaluation of 30 stopping rules which have appeared in the clustering literature, Milligan and Cooper (1985) conclude that the Calinski and Harabasz index (Pseudo F statistic) is most effective, and the Duda and Hart statistic (Pseudo T^2 statistic) is second most effective.

in order to detect more subtle structural change by sharing the same two years like moving average in time series analysis (Table 4.4). For example, groupings in 1979 through 1981 are compared with those in 1980 through 1982 (sharing overlapping years of 1980 and 1981). The group dynamics found are further referenced to the accounting data such as revenue, net income, and productivity. Finally, we analyze longitudinal movement of other firms relative to a couple of designated firms in the industry over time. We develop a grand summary statistic which summarizes stock movements between a firm and a designated firm (i.e. American) over the period of 1979 through 1992 or 15 years. A grand summary statistic is an average of coefficients measuring closeness of stock return movements over 50 weeks or one year.

As emphasized in the previous chapters (Cool (1985) and Fiegenbaum and Thomas (1990)), the assessment of SSTPs is made complex both by temporal changes in competitive behaviors along the strategic dimensions and by changes in the interrelationships among the strategic dimensions. In our exploratory study, we determine an SSTP by comparing pooled and unpooled clustering results over 1 year, 2 years, 3 years, and 5 years. If the grouping structure of 1-year window, say, 1979 (unpooled) is not similar with that of 2-year window, say, 1979-1980 (pooled), we use 1979 as an SSTP. If they are similar, we combine the data of 1979 and 1980, and further compare that of 2-year window, say, 1979-1980 (now, unpooled) and that of 3-year window, say, 1979-1981 (pooled), and so on. In judging whether pooled and unpooled clustering results are similar or not, we use face validity and industry's historical progress instead of statistical criteria such as Bartlett's test (Green, 1978: 169-171) and Hotelling's T^2 test

(Green, 1978: 166-167)[37]. Because the airline industry has been very competitive and dynamic, especially since its liberalization in 1978, the statistical results may not provide in-depth inferences other than the fact that each year's variance matrices and mean vectors are statistically different. Furthermore, the clustering results already contain the information on the equivalence of two sets of variance-covariance matrices.

4.3.3.6 Longitudinal Analysis of Relative Closeness

This section examines longitudinal movement of other firms relative to a couple of designated firms in the industry over the time period of 1979 through 1992. We calculate annual coefficients which represent summary correlation coefficients between a firm and a designated firm over one year. The coefficient can be regarded as a measurement which summarizes closeness of stock return movements over 50 weeks or one year. From the annual coefficients, we can derive average of 15 year coefficients which can be interpreted as grand summary statistic which summarizes stock movements between two firms over the period of 1979 through 1992 or 15 years.

4.4 Results

4.4.1 The nature of the clusters

In order to find SSTPs over the periods of 1979 through 1992, the groups are identified under 1-year, 2-year, 3-year, and 5-year windows. Table 4.2 describes group memberships in the airline industry derived by the stock return method. The first 4

---

[37] Fiegenbaum *et al* (1987) use Bartlett's test to test the equivalence of two sets of variance-

columns present groupings based on 1979 or 1-year (50 weeks), 1979 to 1980 or 2-year (100 weeks), 1979 to 1981 or 3-year (150 weeks), and 1979 to 1983 or 5-year (250 weeks) sample data. The last 4 columns present groupings based on 1992 or 1-year, 1991 to 1992 or 2-year, 1990 to 1992 or 3-year, and 1988 to 1992 or 5-year sample data. Note that the first 4 columns adds base year plus-one, -two, and -four years to the base year of 1979 (i.e. 2-year window being 1979 and 1980), while the last adds base year minus-one, -two, and -four years to the base year of 1992 (i.e. 2-year window being 1992 and 1991). The second 4 columns in the Table 4.2 describe groups under each window in the period of 1981 through 1985 (the base year being 1985 and adding base year minus-one, -two, and -four years), while the third 4 columns describe groups in 1984-88 period (its base year being 1984 and adding base year plus-one, -two, and -four years).

The underlying reason for looking into industry subgroups under different windows at different points of time is that we are interested in the marginal structural changes (by adding one more year) assuming that the industry structure of 1979 (or 1992 in the last case) is given. If there is no significant structural changes in 1980 in comparison with that of 1979, the structure of the 2-year window (i.e. 1979 to 1980) will be more or less similar to that of the 1-year window, say 1979. This implies that the 2 year window does not stretch into a period of evolutionary instability. Thus, we may conclude that industry substructure stays constant over the 2 year period, and the period belongs to the same SSTP. Note that up to the point when groups are identified over various sample windows, no subjective and arbitrary manipulation of data and variables are made, and the same grouping method is used for each sample time period: market driven 'hard' stock returns have been systematically used to detect subgroups under different windows at the

---

covariance matrices and Hotelling's T^2 test to test the equivalence of two sets of mean vectors.

different points of time.

In the first 4 columns (1979-1983) which represent the post 5-year period since 1978's liberalization in the airline industry, the leader group becomes obvious in the 3-year and 5-year window. For example, American, United, Delta, Northwest, and TWA belong to the leader group in the 3- and 5-year windows in addition to 1- and 2- year windows. Some non-market leaders like Frontier, Braniff, and Ozark are grouped to the leader group in the 1- and/or 2-year window, but they are not classified as leaders in the 3-year and 5-year windows. Other non-market leaders like Tiger, Pedimont, and Southwest Airlines are never classified as leaders, and they are unstable across different time windows. During the period 1979-1983, the average number of firms in the industry is 16 which is 4 less than that of period 1981-1985, but 6 more than that of period 1988-1992.

In the 2nd 4 columns or during the period of 1981 to 1985, even though the term becomes longer (or as we expand time frame from 1985 toward industry's liberalization of year 1978), the leader group does not become obvious. Although obvious leading firms are not grouped into the leader group, Hawaiian and Aloha are grouped together all the time across all windows. In addition, the number of firms competing in the industry has been maximized in this period. As shown in Table 4.3 (50 weeks window), between 1980 and 1985, the average number of firms existing in the industry is 22, and this number is larger than any other periods since 1978. In the 150 weeks window, Table 4.4 also shows that the 1980-85 period has the highest number of firms.

It may be inferred from these facts that these periods reflect when firms in the industry explored various possible ways for survival or success under an increasingly competitive and uncertain environment (r-type). As a matter of fact, since the liberalization of 1978, more firms have entered into the airline market which once was lucrative but restricted. Among the leaders, the competition became more fierce in the fight to maintain market share. In addition, the frequent flyer program was introduced in this period. American was the first airline to launch the frequent flyer program in 1981, using the SABRE system to keep track of mileage. However, this successful program was soon replicated by major competitors, and in the same year or 1981, United countered with its own program followed by TWA, Delta, Northwest, and Continental.

In the 3rd 4 columns (1984-88) which include a consolidating period of 1986-1988, under the 250 week window, the leader group becomes obvious (American, Delta, United, US Air, and Northwest) and the number of firms in the industry decreases from 21 to 12. Under the 50, 100, and 150 week windows, the leader group includes some of the non-market leaders such as Pedimont and Southwest. In the 4th 4 columns (1988-1992) which is a period post to consolidation, overall industry structure stays stable across different time span.

Since 1986, mergers and acquisitions have become prevalent in the industry; in 1986, Continental bought People Express and Frontier Airline, and Delta bought Los Angeles based Western Airline; Alaska bought Long Beach-based Jet America Airline and Seattle-based Horizon Air Industry; Northwest acquired Republic Airline in 1987; American acquired Nashville Eagle Commuter Airline (see Table 4.5). This period can be inferred as a consolidating period in which competitors survive through mergers and acquisitions of less competitive airlines (k-type). By 1987, the number of firms diminishes from 22 to 13 (see Tables 4.3 and 4.4).

Table 4.3 describes groups under the 50 week window over the period of 1978 to 1992. As mentioned earlier, the number of firms increases to around 22 firms until 1985, and stabilizes rapidly to around 10 firms after 1985. Another finding is that the leader group becomes obvious and stable after 1985 even in the 1-year window. Some niche-specific firms like Alaska, Hawaiian, and Aloha have been consistently grouped together from the early 1980s.

Table 4.4 describes groups under the 150 week window over the period of 1979 to 1992. In order to observe more subtle structural changes, each window shares the same two years by deleting the first year and adding one year (i.e. moving average in time series analysis). For example, the first column represents groupings from 1979 through 1981, and the second is from 1980 through 1982 (sharing overlapping years of 1980 and 1981).

In this table, the number of firms drops sharply from 1984 to 1986 and 1985 to 1987, and stabilizes rapidly around 10 thereafter. Another finding is that from the 1981-1983 window to 1983-1985 which is a r-typed period, some of the non-market leaders are classified into the leader group, but are excluded from the leader group after 1986. In the first 5 windows (79-81 window through 83-85 window), we can observe that the leader group has become more competitive and crowded and that the other non-leaders have become unstable. The exception is that strong niche-focused firms such as Aloha and Hawaiian are stable. These findings are similar to those found in the 50 week window without overlapping years (see Table 4.3).

Table 4.6 shows sales volume over the period from 1984 to 1992 for selected firms. In terms of average annual revenue, American ($9,223 MIL) and United possess ($9,035MIL) the largest market share in the industry followed by Delta ($6,924MIL), British ($6,467MIL), and Northwest ($5,477MIL). US Air realizes a middle-to-low market share until 1987, but boost its market share to a upper middle level afterwards. Comparing the firms in the leader group in the period from 1984-1992 (3rd and 4th 4 Columns in Table 4.2), American, United, Delta, and Northwest are consistently in the same group and in the highest hierarchy within the group. Although British has the 4th largest market share, it has not been grouped into the leader group. In the case of Southwest, although it possesses small market share ($1,011MIL), it is grouped among the leaders, but in the lowest hierarchy within the group. It seems that the stock return method counts the sales volume to some degree, but not totally.

Table 4.7 displays net incomes over the period of 1984 to 1992 for selected firms. On average, British ($279MIL), American ($137MIL), and Delta ($110MIL) realize the largest net income in the industry. Southwest ($53MIL) stays profitable even in the 1990s when most domestic firms are not doing well. Although United and Northwest achieve the largest market share in revenues, United and Northwest realize average net income (loss) of $57 and ($213), respectively. Like other major domestic airlines, they suffered big losses since 1990. Comparing the firms in groups in the period of 1988-1992 (4th 4 Columns in Table 4.2), British is obviously separated from American and Delta although it achieves comparable revenue and net income. On the other hand, United, Northwest, and Southwest are grouped together with American and Delta, although in the lowest hierarchy within the group.

In order to see productivity in conjunction with net incomes, Table 4.8 presents Income as % of sales over the period of 1984 to 1992. Southwest (5.7%) and British (4.6%) are the most productive followed by Alaska(2.5%), American (2.4%), and Delta (2.3%). Other major domestic firms in the leader group show low to moderate productivity or less than 1%. Comparing the firms in groups in the period of 1988-1992 (4th 4 Columns in Table 4.2), British is grouped together with KLM (2.0%), and is separated from Southwest.

4.4.2 Longitudinal Analysis of Relative closeness

This section examines longitudinal movement of other firms relative to a couple of designated firms in the industry over the time period of 1979 through 1992. Since American Airlines and Alaska Airlines are distinguishable from the stand point of face validity, we will examine their cases.

Table 4.9 presents longitudinal movements of other firms from the perspective of American Airlines. The coefficients in the table or points in the graph represent summary correlation coefficients between a firm and American Airlines over that year. For example, 0.0887 in the first cell of the table represents the average correlation coefficient of stock returns between American Airlines and Alaska Airlines for the 50 week period in 1979. The coefficient can be regarded as a measurement which summarizes closeness of stock return movements over 50 weeks or one year. The last column in the table represents average of 15 year coefficients. It can be interpreted as grand summary statistic which summarizes stock movements between a firm and American Airlines over the period of 1979 through 1992 or 15 years.

From the perspective of American Airlines as shown in Table 4.9, there are three firms, namely Delta, United, and Northwest, whose grand correlation coefficients are greater than .5, namely .5789, .5659 and .5107, respectively. Considering that the coefficient is a summary statistic over the 15 years, their stock returns have comoved very tightly over the 15 year- period. On the other hand, British Airways and KLM have grand correlation coefficients of .0327 and .1784, respectively. While their sales volumes (see Table 4.6) and net incomes (Table 4.7) are near the group of American, Delta, and United, nonetheless, the two airlines are clearly distinguishable from large trunk airlines. Furthermore, American Airlines easily differentiates itself from small regional airlines such as Alaska (grand coefficient of .2135), Aloha (.1111), and Hawaiian (.0632).

Table 4.10 presents longitudinal movements of other firms from the perspective of Hawaiian Airlines over the period from 1980 through 1986 (stock return data for the airline is not available for other years). As shown in Table 4.10, Aloha Airlines has the highest grand correlation coefficients of .2827, and the average of grand correlation coefficients of .0803 is much lower than that in American Airlines case of .3087 (see Table 4.9). This fact may imply that Hawaiian Airlines is a niche-specific or -pursuing airline, and that as judged by those buying and selling its stock, is affected by rather idiosyncratic environmental factors.

4.5 Discussion and Conclusion

The findings from chapter 2 and 3 demonstrate that the stock return method is an effective method to identifying industry substructure. It is shown that groups found provide clear face validity and statistical validity, and the results are objective and replicable. In this chapter, the stock return method is further developed to analyze longitudinal structural dynamics. The stock return method is extended from a static view to a dynamic one enabling analysis of longitudinal changes of industry substructure. The dynamic approach is applied to the airline industry over the period of 1979 to 1992, and the results are referenced with the industry's historical progress and accounting sales and income data. Furthermore, relative closeness of stock movements between two firms is analyzed over the time period.

There are two motivations for this chapter. First is to enhance the validity of the stock return method by applying the method in a longer time period. If this method can effectively identify reliably and validly separated industry substructure, the stock return method should be able to produce longitudinally stable groups over time which can confirm industry's historical progress (i.e. 15 year time span). Since groups are derived objectively and are replicable without the researcher's subjective choice of methods or variables, results which confirm industry's historical progress (based on actual facts) over a long time span ensure a high level of validity for the stock return method. Second is to fulfill the need to develop an objective and replicable method to analyze longitudinal changes in industry substructure. Since the stock return method determines subgroups based on more objective and replicable market-driven equilibrium stock returns rather than on arbitrarily chosen strategic dimensions by researchers, the stock return method is worth further development.

We find that the stock return method can be an effective instrument to analyzing longitudinal structural dynamics. In our particular sample, the results confirm the industry's historical progress. During the period of 1979-1985 (1st, 2nd, and part of 3rd 4 columns in Table 4.2), the number of firms in the industry increase, and the industry leader group does not always include only obvious leading firms such as American, Delta, and United. On the other hand, during the period of 1986-1992 (part of 3rd and 4th 4 columns in Table 4.2), the number of firms in the industry decrease to 10 and the industry substructure becomes very consistent. It appears that liberalization has created lower entry barriers to the industry and fierce competition among the firms in the industry (r-type). Consequently, less competitive firms become obsolete, and die out. Competitive firms became more competitive through acquiring less competitive firms (k-type). Niche-specific firms who are efficient survive even in the most competitive environment. In the long run, the firms decrease in number, and the competition has become more intense since deregulation. These facts confirm the paradigm of Industrial Economics that industrial liberalization is better than restricted industry monopoly from the perspective of social welfare because competition drives firms to be efficient.

We also find that although they do not perfectly explain the longitudinal dynamics of groups, accounting data such as market share or productivity support our findings. American and Delta achieve the largest market share and net income, and they are grouped into the leader group. However, British is not grouped with the leaders in spite of its largest market share and net income. As for United and Northwest, they realize the largest market share but their net income is not the largest. Nonetheless, they are grouped into the leaders. On the other hand, Southwest possesses the smallest market share and the largest net income, and is grouped together with leaders. As for productivity, Southwest and British are the most productive. Their productivity is two times higher than that of American and Delta, and five times higher than that of other major domestic firms.

From the longitudinal analysis of relative closeness, we find that the results from the stock return method are valid and robust over a longer time span. The leading firms like American, United, Delta, and Northwest show the highest grand correlation coefficients, meaning that their stock movements are very close over a longer time period. In addition, niche-specific firms like Hawaiian and Aloha have the highest grand correlation coefficients, but their grand correlation coefficients are not high with respect to the leading firms. This fact suggests that the stock return method is an effective method to identifying industry substructure even over a longer time span.

In the American case, Delta, United, and Northwest have moved closely over the 15 year period, their grand correlation coefficients being greater than 0.5. Considering that it is a summary statistic over the 15 years (ranging from -1 to 1), it is surprisingly significant that the grand correlation coefficient over 15 year period is greater than 0.5. On the other hand, British Airways and KLM have grand correlation coefficients of .0327 and

.1784, respectively. While their sales volumes (see Table 4.6) and net incomes (Table 4.7) are near the group of American, Delta, and United, nonetheless, the two airlines are clearly distinguishable from the large trunk airlines. Furthermore, American Airlines easily differentiates itself from small regional airlines such as Alaska (grand coefficient of .2135), Aloha (.1111), and Hawaiian (.0632). In the Hawaiian case, Aloha has the highest grand correlation coefficients of .2827, suggesting that their stock return movements are similar. On the other hand, the average of grand correlation coefficients of .0803 is much lower than the American Airlines case of .3087 (see Table 4.9). This fact may imply that Hawaiian Airlines is a niche-specific or -pursuing airline.

Although the stock return method is an effective instrument for analyzing longitudinal structural dynamics and the results from the stock return method are valid and robust over a longer time span, there still remain some limitations:

1. *No* R *statistic.* We would have strongly preferred to use Johnson's (1994) method, based on Friedman and Rafsky's R, but stock returns call for the product-moment resemblance coefficient and the R coefficient has only been tested out for difference coefficients. Our use of the historically-observed consistencies of results is a somewhat oblique approach to testing for statistical significance.

2. *Local optima.* Clustering methods run the risk of producing locally optimized clusters rather than globally optimized ones. Since no clustering package is available to use as a randomized initialization procedure, we can not avoid the local optimization possibility. This could lead to more overlap among the groups than is actually true for the data.

While recognizing limitations, we believe that the stock return method may resolve meaningful issues in the field of strategy. Future research includes applying the stock return method to examine the relationship between groups and groups' performances as well as between group members and their performances. A recognized difficulty in pursuing these issues has been finding a firm-specific risk-adjusted profitability measure; the standard deviation of returns on sales or returns on assets has been used to measure risk (Cool and Shendel, 1988; Cool, Dierickx, and Jemison, 1989). Elimination of market-evaluated financial risk from profitability could provide better insights into these issues.

Another extension is to conduct a longitudinal analysis over a long-term time horizon. Although chapter 4 attempts to explore this extension, it would be particularly interesting to look into the locus of groups' or group members' structural moves. Some important issues in this analysis may include the following; the sustainability of the relationship between group membership and profitability over time; the cause of structural changes, if any, due to external environmental conditions or internal innovations; the presence of first-mover advantages (in the form of superior profitability); and if so, the sustainability of these advantages over a long-term period. The analysis of structural transition over time based on the stock return method could resolve such meaningful issues in the field of strategy.

Finally, we draw several conclusions from this study. First, the stock return method can effectively identify industry subgroups as maintained in chapter 2 and 3. The findings show that the groups found are valid and robust even over a longer period. The evidences confirm that industry substructure can be reliably and validly separated, and that longitudinal substructure has been developed in accordance to the historical progress. Coupled with the results from chapter 2 and 3, the results from this chapter suggest that the stock return method can effectively identify industry subgroups with face and statistical validity. Second, the stock return method is an objective and replicable method of analyzing longitudinal changes in industry substructure. The historically consistent results from the stock return method using 'hard' market-equilibrium data rather than on arbitrarily chosen strategic dimensions by researchers ensure the method's objectivity and replicability.

Tables

TABLE 2.1: Summary Statistics for Groups

	Group 1	Group 2	Group 3	Group 4	Total
No. firms	17	34	24	19	94
Total Asset	504.94 (181.00)	242.76 (112.00)	84.42 (174.23)	28.52 (33.49)	206.44 (1024.76)
Number of Employees	9,043 (3,030)	5,238 (2,008)	2,847 (607)	793 (110)	4,417 (17,832)
Return on Assets(ROA)	0.083 (0.078)	0.070 (0.133)	0.072 (0.067)	0.046 (0.146)	0.068 (0.113)
Return on Equity(ROE)	0.132 (0.204)	0.125 (0.176)	0.095 (0.216)	0.059 (0.380)	0.105 (0.242)
Sales by Total Asset	1.54 (0.59)	1.54 (0.47)	1.49 (0.36)	1.40 (.48)	1.50 (0.47)
Sales per Employee	52.88 (17.84)	47.63 (26.24)	43.54 (14.02)	50.78 (14.77)	48.18 (20.03)
Total Operating Divisions	5.24 (6.86)	5.18 (10.04)	4.08 (5.03)	5.05 (4.80)	4.88 (7.41)
Number Plants & Facilities	4.00 (4.54)	3.62 (7.55)	3.38 (6.16)	1.47 (1.90)	3.19 (5.89)
Specialization Ratio	0.86 (0.17)	0.91 (0.14)	0.88 (0.20)	0.91 (0.13)	0.89 (0.16)

Mean and (STD) for descriptive characteristics of groups
Total number of firms = 94

TABLE 2.2: Statistics for Canonical Discriminant Analysis

Can. Ftn.	Adj. C. C.	Approx. Std. Err.	Squared C. C.	Eigenvalue	Proportion
CAN 1	0.8514	0.0163	0.8429	5.3656	0.4625
CAN 2	0.8080	0.0218	0.7897	3.7554	0.3237
CAN 3	0.7405	0.0298	0.7127	2.4806	0.2138

C. C. means Canonical Correlation.

TABLE 2.3a: Multivariate Statistics for Groups w.r.t. 67 Taxonomic Characters

Statistics	Value	F	Num DF	Den DF	p- value
Wilks' Lambda	0.0095	1.43	198	75.91	0.0371
Pillai's Trace	2.3453	1.47	198	81	0.0249
Hotelling-Lawley Trace	11.6016	1.39	198	71	0.0556
Roy's Greatest Root	5.3656	2.20	66	27	0.0129

Num DF is the degree of freedom of numerator.
Den DF is the degree of freedom of denominator.

TABLE 2.3b: F Approximations and p-values w.r.t. Canonical Functions

	Value	Approx. F	Num DF	Den DF	p-value
CAN 1	0.0095	1.4288	198	75.91129	0.0371
CAN 2	0.0604	1.2274	130	52	0.2022
CAN 3	0.2873	1.0465	64	27	0.4623

Num DF is the degree of freedom of numerator.
Den DF is the degree of freedom of denominator.

Table 3.1: The Sampled Companies and their Industries

Banking Industry	**Oil Industry**	**Airline Industry**
$N_x = 12$	$N_z = 20$	$N_A = 9$
Citicorp (6711)	Amerada Hess Corp (2911)	A M R Corp (4511)
BankAmerica Corp. (6711)	Ashland Oil Inc (2911)	Delta Air Lines Inc (4511)
NationsBank Corp. (6712)	Atlantic Richfield Co (2911)	Alaska Airgroup Inc (4511)
Chemical Banking Corp. (6025)	Chevron Corp (2911)	British Airways PLC (4511)
Morgan J.P. & Co Inc. (6711)	Crown Centruy Petroleum Corp (2911)	K L M Royal Dutch AIRLS (4511)
Chase Manhattan Corp. (6025)	Diamond Shamrock Inc (2911)	Southwest Airlines Co (4511)
Bankers Trust N.Y. Corp (6025)	Exxon Corp (2911)	U A L Corp (4512)
Banc One Corp. (6711)	Holly Corp (2911)	United States Air Group Inc (4511)
PNC Financial Corp (6025)	Howell Corp (2911)	WorldCorp Inc (4511)
First Chicago Corp (6025)	KERR McGee Corp (2911)	
Wells Fargo & Co. (6025)	Mobil Corp (2911)	
First Interstate Bancorp (6711)	Murphy Oil Corp (2911)	
	Norsk Hydro A S (2911)	
	Phillips Petroleum Co (2911)	
	Quaker State Corp (2911)	
	Spelling Entertainment Group Inc (2911)	
	Sun Inc (2911)	
	Tesoro Petroleum Corp (2911)	
	Tosco Corp (2911)	
	Total Petroleum N. America Ltd. (2911)	

The 4-digit number in the parentheses is the 4-digit SIC for the company

Table 3.2: Pseudo F and Pseudo T^2 By Each Window

	50 weeks		100 weeks		150 weeks		250 weeks	
#Groups	F	T^2	F	T^2	F	T^2	F	T^2
1		11.8		8.9		9.4		9.3
2	11.8	5.7	8.9	6.1	9.4	8.4	9.3	6.4
3	10.0	3.9	8.6	3.5	8.8	5.6	9.0	4.2
4	9.3	3.7	7.9	2.6	8.6	2.9	8.5	1.9
5	9.3	2.8	7.4	1.9	8.0	3.5	7.3	1.8
6	8.9	2.7	6.8	2.3	7.4	3.8	6.7	3.3
7	8.6	2.6	6.5	1.8	7.0	1.6	6.3	1.5
8	8.5	2.7	6.3	3.6	6.7	1.6	6.0	1.5
9	8.3	5.3	6.2	1.6	6.4	1.3	5.7	1.6

TABLE 3.3: Industry Classification By Each Window (3 Clusters)

Number of Groups = 3

N=41 Firms

	100 WKS ('91-'92)	150 WKS ('90-'92)	250 WKS ('88-'92)
CL1	A M R CORP	A M R CORP	A M R CORP
	U A L CORP	DELTA AIRLINES INC DE	DELTA AIRLINES INC DE
	DELTA AIRLINES INC	BRITISH AIRWAYS PLC	BRITISH AIRWAYS PLC
	BRITISH AIRWAYS PLC	K L M ROYAL DUTCH AIRLS	K L M ROYAL DUTCH AIR
	K L M ROYAL DUTCH AIRLS	ALASKA AIR GROUP INC	ALASKA AIR GROUP INC
	ASHLAND OIL INC*	US AIR G INC	US AIR G INC
	DIAMOND SHAMROCK INC*	U A L CORP	U A L CORP
	CROWN CENTURY PETRO*	SOUTHWEST AIRLINES CO	SOUTHWEST AIRLINES CO
	TESORO PETROLEUM CORP*		
	ALASKA AIR LINES INC		
	US AIR G INC		
	SUN INC*		
	NORSK HYDRO A S*		
	SPELLING ENTERTAINMENT*		
	BANC ONE CORP*		
	SOUTHWEST AIRLINES INC		
	TOTAL PETROLEUM NORTH AM*		
	QUAKER STATE CORP*		
CL2	CHASE MANHATTAN	CHASE MANHATTAN	CHASE MANHATTAN
	CHEMICAL BANK	CHEMICAL BANK	CHEMICAL BANK
	FIRST INTERSTATE	FIRST INTERSTATE	FIRST INTERSTATE
	WELLS FARGO	WELLS FARGO	WELLS FARGO
	CITICORP	CITICORP	CITICORP
	FIRST CHICAGO	BANKAMERICA	BANKAMERICA
	NATIONSBANK	FIRST CHICAGO	FIRST CHICAGO
	PNC BANK CORP	NATIONSBANK	NATIONSBANK
	BANKAMERICA	BANKER'S TRUST	BANKER'S TRUST
	BANKER'S TRUST	JP MORGAN	JP MORGAN
	JP MORGAN	BANC ONE CORP	BANC ONE CORP
		PNC BANK CORP	PNC BANK CORP
CL3	ATLANTIC RICHFIELD CO	CHEVRON CORP	CHEVRON CORP
	MOBIL CORP	MOBIL CORP	MOBIL CORP
	CHEVRON CORP	ATLANTIC RICHFIELD CO	ATLANTIC RICHFIELD CO
	KERR MCGEE CORP	PHILLIPS PETROLEUM CO	PHILLIPS PETROLEUM CO
	AMERADA HESS CORP	EXXON CORP	EXXON CORP
	PHILLIPS PETROLEUM CO	AMERADA HESS CORP	AMERADA HESS CORP
	EXXON CORP	KERR MCGEE CORP	KERR MCGEE CORP
	MURPHY OIL CORP	MURPHY OIL CORP	MURPHY OIL CORP
		DIAMOND SHAMROCK INC	DIAMOND SHAMROCK IN
		TOSCO CORP	TOSCO CORP
		TESORO PETROLEUM CORP	TESORO PETROLEUM C
		TOTAL PETROLEUM NORTH A	TOTAL PETROLEUM NO
		SUN INC	SUN INC
		CROWN CENTURY PETROLEU	CROWN CENTURY PETR
		HOLLY CORP	HOLLY CORP
		ASHLAND OIL INC	ASHLAND OIL INC
		HOWELL CORP	HOWELL CORP
		SPELLING ENTERTAINMENT	SPELLING ENTERTAIN
		NORSK HYDRO A S	NORSK HYDRO A S
		QUAKER STATE CORP	QUAKER STATE CORP
		WORLDCORP INC*	WORLDCORP INC*
* Misspecification	10	1	1

TABLE 3.4: Subgroup Classification By Each Window (9 Clusters)

Number of Groups = 9
N=41 Firms

	50 WKS ('92)	100 WKS ('91-'92)	150 WKS ('90-'92)	250 WKS ('88-'92)
CL1	ATLANTIC RICHFIELD CO	ATLANTIC RICHFIELD CO	CHEVRON CORP	CHEVRON CORP
	MOBIL CORP	MOBIL CORP	MOBIL CORP	MOBIL CORP
	CHEVRON CORP	CHEVRON CORP	ATLANTIC RICHFIELD CO	AMERADA HESS CORP
	KERR MCGEE CORP	AMERADA HESS CORP	PHILLIPS PETROLEUM CO	ATLANTIC
	AMERADA HESS CORP	KERR MCGEE CORP	EXXON CORP	PHILLIPS PETROL CO
	PHILLIPS PETROL CO	PHILLIPS PETROLEUM CO	AMERADA HESS CORP	EXXON CORP
	EXXON CORP	EXXON CORP	KERR MCGEE CORP	KERR MCGEE CORP
	MURPHY OIL CORP	MURPHY OIL CORP	MURPHY OIL CORP	MURPHY OIL CORP
				NORSK HYDRO A S
CL2	A M R CORP	A M R CORP	A M R CORP	A M R CORP
	U A L CORP	U A L CORP	DELTA AIRLINES INC DE	DELTA AIRLINES INC DE
	DELTA AIRLINES INC	DELTA AIRLINES INC DE	ALASKA AIR GROUP INC	U A L CORP
	ALASKA AIR LINES INC	ALASKA AIR GROUP INC	US AIR G INC	SOUTHWEST AIRLN CO
	SOUTHWEST AIRLN CO	US AIR G INC	U A L CORP	US AIR G INC
	US AIR G INC		SOUTHWEST AIRLINES CO	ALASKA AIR GRP INC
CL3	CHASE MANHATTAN	CHASE MANHATTAN	CHASE MANHATTAN	CHASE MANHATTAN
	CHEMICAL BANK	CHEMICAL BANK	CHEMICAL BANK	CHEMICAL BANK
	NATIONSBANK	FIRST INTERSTATE	FIRST INTERSTATE	FIRST INTERSTATE
	CITICORP	WELLS FARGO	WELLS FARGO	WELLS FARGO
	FIRST CHICAGO	CITICORP	CITICORP	CITICORP
	WELLS FARGO	FIRST CHICAGO	BANKAMERICA	FIRST CHICAGO
	BANKAMERICA	NATIONSBANK	FIRST CHICAGO	BANKAMERICA
	FIRST INTERSTATE	PNC BANK CORP	NATIONSBANK	NATIONSBANK
	PNC BANK CORP	BANKAMERICA	PNC BANK CORP	PNC BANK CORP
CL4	BANKER'S TRUST	BANKER'S TRUST	BANKER'S TRUST	BANKER'S TRUST
	JP MORGAN	JP MORGAN	JP MORGAN	JP MORGAN
	BANC ONE CORP		BANC ONE CORP	BANC ONE CORP
	HOLLY CORP*			
CL5	QUAKER STATE CORP	BRITISH AIRWAYS PLC	BRITISH AIRWAYS PLC	BRITISH AIRWAYS PLC
	TESORO PETROLEUM CORP	K L M ROYAL DUTCH AIRLS	K L M ROYAL DUTCH AIRLS	K L M ROYAL DUTCH AIRLS
	K L M R DUTCH AIRLS*	TOTAL PETROL NORTH AM*		
	TOTAL PETROL NORTH AM			
CL6	DIAMOND SHAMROCK INC	ASHLAND OIL INC	DIAMOND SHAMROCK INC	DIAMOND SHAMROCK INC
	TOSCO CORP	DIAMOND SHAMROCK INC	TOSCO CORP	TOSCO CORP
	NORSK HYDRO A S	SUN INC	SUN INC	SUN INC
		TOSCO CORP	ASHLAND OIL INC	ASHLAND OIL INC
				CROWN CENTURY PETROLEUM
CL7	CROWN CENTURY PETROL	CROWN CENTURY PETROL C	TESORO PETROL CORP	TOTAL PETROLEUM NORTH AM
	SUN INC	TESORO PETROLEUM CORP	TOTAL PETROL NORTH AM	SPELLING ENTERTAINMENT G
	BRITISH AIRWAYS PLC*	HOLLY CORP	CROWN CENTURY PETROLEUM	HOLLY CORP
		HOWELL CORP	HOLLY CORP	
		WORLDCORP INC*		
CL8	ASHLAND OIL INC	NORSK HYDRO A S	HOWELL CORP	TESORO PETROLEUM CORP
	WORLDCORP INC*	SPELLING ENTERTAINMENT	SPELLING ENTERTAINMENT G	QUAKER STATE CORP
			WORLDCORP INC*	WORLDCORP INC*
CL9	HOWELL CORP	BANC ONE CORP*	NORSK HYDRO A S	HOWELL CORP
	SPELLING ENTERTAINMENT	SOUTHWEST AIRLINES CO*	QUAKER STATE CORP	
		QUAKER STATE CORP		
	4	4	1	1

* Misspecification

Table 3.5: Eigenvalue and Proportion of Principal Components (PRIN1-PRIN5)

	50 WKS ('92)		100 WKS ('91-'92)		150 WKS ('90-'92)		250 WKS ('88-'92)	
prin1	16.43	.40	13.90	.33	14.21	.35	14.72	.36
prin2	5.14	.13	6.72	.16	6.12	.15	6.15	.15
prin3	3.73	.09	3.34	.08	3.53	.09	3.07	.07
prin4	2.85	.07	2.91	.07	3.00	.07	2.03	.05
prin5	2.42	.06	2.03	.04	1.79	.04	1.64	.04

TABLE 4.1: List of Sample Firms (N=30)

COMPANY NAME	BEG-END*	SIC
AIRCAL INC	850102-870429	4511
AMERICAN AIR LINES INC	620702-921231	4511
ALASKA AIRGROUP INC	620702-921231	4511
ALOHA AIRLINES INC	791214-861226	4511
BRANIFF INT'L CORP	620702-820527	4511
BRITISH AIRWAYS PLC	870211-921231	4511
CONTINENTAL ARLNS HLDGS	780406-920320	4512
DELTA AIRLINES INC DE	620702-921231	4511
EASTERN AIRLINES INC	620702-861123	4511
FRONTIER AIRLINES INC	640415-851121	4511
HAWAIIAN AIRLINES INC	740523-921231	4511
JET AMERICAN ARLNS INC	841003-861226	4511
KLM ROYAL DUTCH ARLNS	620702-921231	4511
MGM GRAND INC	891213-921231	4512
MIDWAY AIRLINES INC	880609-911001	4512
NORTHWESTERN ARLNS INC	620702-890726	4511
OZARK AIRLINES INC	670508-860915	4511
PAN AM CORP	620702-910925	4511
PIEDMONT AVIATION INC	780925-871104	4511
REPUBLIC AIRLINES INC	730522-860812	4511
SEABOARD WORLD ARLNS INC	620702-800930	4511
SOUTHWEST AIRLINES CO	751024-921231	4511
TIGER INT'L INC	620702-890215	4511
TRANS WORLD ARLNS INC	830303-881024	4511
UNITED AIR LINES CORP	620702-921231	4512
US AIR GROUP INC	620702-921231	4511
W T C INT'L NV	700709-870903	4511
WESTAIR HOLDING INC	881025-920529	4512
WESTERN AIRLINES INC	620702-861218	4511
WORLDCORP INC	670424-921231	4511

* BEG-END is the beginning and ending dates of CRSP data available. For instance, AirCal's CRSP data is available from January 2 of 1985 through April 29 Of 1987.

TABLE 4.2: Groups in the Period of 1979-1992

	60WKS 79	100WKS 79-80	150WKS 79-81	250WKS 79-83
I	AMRCORP UALCORP DELTA NWAINC TWA CONT OZARK WESTERN REPUBLIC FRONTIER BRANIFF	AMRCORP UALCORP DELTA NWAINC TWA USAIR BRANIFF FRONTIER	AMRCORP UALCORP DELTA NWAINC TWA	AMRCORP UALCORP NWAINC DELTA TWA USAIR
II	TIGER KLM	CONT WESTERN REPUBLIC TIGER OZARK PEDMONT	CONT WESTERN PEDMONT	FRONTIER OZARK PEDMONT WESTERN SOUTHWEST
III	USAIR PEDMONT	SOUTHWEST	REPUBLIC USAIR FRONTIER OZARK BRANIFF TIGER	REPUBLIC TIGER
IV	SOUTHWEST SEABOARD	WTC	SOUTHWEST WTC	WTC
V	WTC			
No of Firms	18	16	16	14
No of Groups	5GROUPS	4GROUPS	4GROUPS	4GROUPS

	60WKS 85	100WKS 84-85	150WKS 83-85	250WKS 81-85
I	AMRCORP UALCORP DELTA EASTERN REPUBLIC PEDMONT SOUTHWEST PAN AM KLM WORLDCORP	AMRCORP DELTA UALCORP NWAINC OZARK PEDMONT USAIR SOUTHWEST TWA	AMRCORP UALCORP DELTA USAIR NWAINC PEDMONT SOUTHWEST OZARK ALASKA TWA	AMRCORP UALCORP DELTA USAIR NWAINC OZARK PEDMONT TWA SOUTHWEST ALASKA
II	USAIR TWA CONT	EASTERN PAN AM KLM WESTERN REPUBLIC	PAN AM EASTERN WESTERN REPUBLIC CONT WORLDCORP	EASTERN REPUBLIC PAN AM WESTERN KLM
III	NWAINC OZARK WESTERN TIGER Jet American	CONT ALASKA	KLM TIGER	CONT TIGER
IV	ALOHA HAWAIIAN ALASKA	TIGER ALOHA HAWAIIAN WORLDCORP	ALOHA HAWAIIAN	ALOHA HAWAIIAN WORLDCORP
V				
No of Firms	21	20	20	20
No of Groups	4GROUPS	4GROUPS	4GROUPS	4GROUPS

	60WKS 88	100WKS 87-88	150WKS 86-88	250WKS 84-88
I	AMRCORP UALCORP DELTA USAIR NWAINC TWA PEDMONT SOUTHWEST	AMRCORP DELTA UALCORP NWAINC OZARK PEDMONT USAIR SOUTHWEST TWA	AMRCORP DELTA UALCORP USAIR NWAINC SOUTHWEST TWA PEDMONT	AMRCORP DELTA UALCORP USAIR NWAINC
II	CONT KLM WESTERN OZARK REPUBLIC WORLDCORP TIGER	EASTERN PAN AM KLM WESTERN REPUBLIC	ALASKA WESTERN KLM PAN AM CONT TIGER WORLDCORP	ALASKA SOUTHWEST KLM PAN AM TIGER
III	ALASKA PAN AM EASTERN FRONTIER	CONT ALASKA	ALOHA HAWAIIAN	CONT WORLDCORP
IV	HAWAIIAN ALOHA	TIGER ALOHA HAWAIIAN WORLDCORP		
V				
No of Firms	21	20	17	12
No of Groups	4GROUPS	4GROUPS	3GROUPS	3GROUPS

	60WKS 92	100WKS 91-92	150WKS 90-92	250WKS 88-92
I	AMRCORP UALCORP DELTA USAIR	AMRCORP UALCORP DELTA ALASKA USAIR SOUTHWEST	AMRCORP UALCORP DELTA ALASKA USAIR SOUTHWEST	AMRCORP DELTA UALCORP SOUTHWEST USAIR ALASKA
II	BRITISH KLM WORLDCORP	BRITISH KLM	BRITISH KLM	BRITISH KLM
III	ALASKA SOUTHWEST	WORLDCORP	WORLDCORP	WORLDCORP
IV	MGM	MGM	MGM	
V				
No of Firms	10	10	10	8
No of Groups	4GROUPS	4GROUPS	4GROUPS	3GROUPS

TABLE 4.3: Groups under 50 Week Window

	77	78	79	80	81	82	83	84
I	AMR CORP UAL CORP DELTA US AIR NWA INC TWA CONT WESTERN FRONTIER BRANIFF SOUTHWEST HAWAIIAN EASTERN TIGER	AMR CORP UAL CORP DELTA NWA INC TWA CONT OZARK WESTERN REPUBLIC FRONTIER BRANIFF	AMR CORP UAL CORP DELTA US AIR NWA INC TWA CONT OZARK WORLDCORP EASTERN BRANIFF TIGER	AMR CORP UAL CORP DELTA US AIR NWA INC TWA CONT PEDMONT SOUTHWEST OZARK TIGER REPUBLIC FRONTIER HAWAIIAN WTC	AMR CORP DELTA ALOHA WESTERN OZARK PEDMONT SOUTHWEST FRONTIER HAWAIIAN	AMR CORP UAL CORP DELTA US AIR NWA INC TWA PEDMONT SOUTHWEST CONT OZARK ALASKA FRONTIER	AMR CORP UAL CORP DELTA US AIR NWA INC TWA PEDMONT SOUTHWEST	AMR CORP UAL CORP DELTA EASTERN REPUBLIC PEDMONT SOUTHWEST PAN AM KLM WORLDCORP
II	PAN AM REPUBLIC OZARK	TIGER KLM	PAN AM WESTERN REPUBLIC FRONTIER WTC	ALOHA HAWAIIAN	US AIR NWA INC UAL CORP TWA EASTERN REPUBLIC KLM	HAWAIIAN WORLDCORP REPUBLIC WESTERN	CONT KLM WESTERN OZARK REPUBLIC WORLDCORP TIGER	US AIR TWA CONT
III	ALASKA WORLDCORP WTC	US AIR PEDMONT WTC	SOUTHWEST FRONTIER HAWAIIAN ALOHA	ALASKA WORLDCORP KLM BRITISH	ALASKA PAN AM TIGER	PAN AM TIGER EASTERN KLM WTC	ALASKA PAN AM EASTERN FRONTIER	NWA INC OZARK WESTERN TIGER Jet American
IV		SOUTHWEST SEABOARD		PAN AM WESTERN	CONT WORLDCORP WTC		HAWAIIAN ALOHA	ALOHA HAWAIIAN ALASKA
V								
No of Firms	20	18	21	23	22	22	21	21
No of Groups	3GROUPS	4GROUPS	3GROUPS	4GROUPS	4GROUPS	3GROUPS	4GROUPS	4GROUPS

	85	86	87	88	89	90	91	92
I	AMR CORP UAL CORP DELTA CONT	AMR CORP UAL CORP DELTA US AIR NWA INC PEDMONT	AMR CORP DELTA SOUTHWEST NWA INC	AMR CORP DELTA NWA INC UAL CORP US AIR	AMR CORP DELTA ALASKA SOUTHWEST UAL CORP PAN AM	AMR CORP DELTA BRITISH KLM	AMR CORP UAL CORP DELTA SOUTHWEST US AIR	AMR CORP UAL CORP DELTA US AIR
II	US AIR TWA	ALOHA HAWAIIAN CONT SOUTHWEST	UAL CORP TWA	BRITISH CONT PAN AM SOUTHWEST TIGER WORLDCORP	MIDWAY WESTAIR KLM WORLDCORP	CONT WESTAIR MIDWAY SOUTHWEST US AIR	BRITISH KLM WORLDCORP	BRITISH KLM WORLDCORP
III	NWA INC OZARK WESTERN EASTERN PAN AM WORLDCORP TIGER	KLM PAN AM TWA WTC	CONT US AIR	ALASKA KLM	CONT US AIR	UAL CORP WORLDCORP MGM	ALASKA WESTAIR	ALASKA SOUTHWEST
IV	ALOHA HAWAIIAN ALASKA	ALASKA WORLDCORP AIRCAL TIGER	ALASKA TIGER		BRITISH	ALASKA PAN AM	CONT MGM HAWAIIAN	MGM
V			PAN AM WORLDCORP					
No of Firms	22	18	13	13	13	14	13	10
No of Groups	4GROUPS	4GROUPS	5GROUPS	3GROUPS	4GROUPS	4GROUPS	4 GROUPS	4 GROUPS

TABLE 4.4: Groups under 150-Week Window

	150WKS 79-81	150WKS 80-82	150WKS 81-83	150WKS 82-84	150WKS 83-85	150WKS 84-86	150WKS 85-87	150WKS 86-88	150WKS 87-89	150WKS 88-90	150WKS 89-91	150WKS 90-92
I	AMR CORP UAL CORP DELTA N W A INC TWA (LIQ)	N W A INC UAL CORP AMR CORP DELTA TWA (LIQ) EASTERN	AMR CORP US AIR N W A INC UAL CORP DELTA TWA (LIQ) EASTERN OZARK PEDIMONT SOUTHWEST FRONTIER	N W A INC UAL CORP AMR CORP DELTA US AIR OZARK PEDIMONT TWA (LIQ) SOUTHWEST	AMR CORP UAL CORP DELTA US AIR N W A INC PEDIMONT SOUTHWEST OZARK ALASKA TWA (LIQ)	AMR CORP DELTA UAL CORP US AIR N W A INC SOUTHWEST TWA PEDIMONT	AMR CORP DELTA UAL CORP N W A INC SOUTHWEST KLM US AIR	AMR CORP DELTA N W A INC US AIR UAL CORP	AMR CORP UAL CORP KLM	AMR CORP DELTA US AIR SOUTHWEST UAL CORP ALASKA	AMR CORP DELTA UAL CORP SOUTHWEST	AMR CORP UAL CORP DELTA ALASKA US AIR SOUTHWEST
II	CONT WESTERN PEDIMONT	OZARK US AIR REPUBLIC SOUTHWEST PAN AM WTC FRONTIER	PAN AM WESTERN CONT TIGER ALASKA REPUBLIC KLM	ALASKA PAN AM TIGER	PAN AM EASTERN WESTERN REPUBLIC CONT WORLDCORP	ALASKA WESTERN KLM PAN AM CONT TIGER WORLDCORP	PAN AM WORLDCORP	ALASKA TIGER	DELTA SOUTHWEST US AIR CONT	BRITISH KLM CONT	BRITISH KLM CONT	BRITISH KLM
III	REPUBLIC US AIR FRONTIER OZARK BRANIFF TIGER	ALOHA HAWAIIAN	ALOHA HAWAIIAN WORLDCORP	ALOHA WESTERN HAWAIIAN FRONTIER WORLDCORP	KLM TIGER	ALOHA HAWAIIAN	ALASKA TIGER	KLM SOUTHWEST	ALASKA PAN AM	PAN AM	ALASKA WESTAIR HLDG US AIR	WORLDCORP
IV	SOUTHWEST WTC	PEDIMONT WESTERN WORLDCORP	WTC	EASTERN KLM REPUBLIC CONT	ALOHA HAWAIIAN		CONT TWA	CONT PAN AM WORLDCORP	WORLDCORP	WORLDCORP	WORLDCORP	MGM
V		CONT TIGER										
No of firms	16	20	22	21	20	17	13	12	10	11	11	10
No of Groups	4GROUPS	5GROUPS	4GROUPS	4GROUPS	4GROUPS	3GROUPS	4GROUPS	4GROUPS	4GROUPS	4GROUPS	4GROUPS	4GROUPS

TABLE 4.5: Major Events of Airline Company over the Per

TABLE 4.5a

Airlines	prior to 1978	1978	1979	1980	1981	1982	1983	1984	1985	1986
Continental Airlines	• Founded as Varney Speed Airlines in 1934				• Texas Air buys 50% of Continental Air.	• Texas Air buys rest of Continental Air.	• Continental had lost over $500 million between 1978 - 1983. • Lorenzo, maneuvers Continental into Chapter 11 bankruptcy. • Texas Air buys Eastern Air.			• Texas Air buys People Express Air and Frontier Air.
British Airways	• Born as Imperial Airways in 1924, as a merge of 4 private airlines by the British government • Three private UK airlines merged in 1935 to form British Airways, which shared European service with Imperial until 1939, when the two were combined to form state-owned British Overseas Airways Corporation. • In 1972, the government combined BOAC and BEA (British European Airways) to form British Airways. • BA and Air France jointly pioneered supersonic passenger service in 1976.					• Supersonic passenger service (the Concorde) in 1976, left BA with a loss of $337 million in '82.	• Former Avis president Colin Marshall became CEO in '83, reduced manpower, sold planes, and pared the airline's route network, building BA into one of the world's most profitable airlines.			
American Airlines (AMR)	• In 1929, Sherman Fairchild create a NY City holding company called The Aviation Corp (AVCO) By 1930, AVCO owned about 85 small airlines. • AVCO created American Airways in 1930. • AVCO splits its aircraft making and trans. division, resulting in Amer.Airlines. Through stocks, it bought Amer. Airways. • American surpasses United as leading US airline in 1930. •1936: DC-3 introduced and is first commercial airline to pay it's way on passenger revenues alone. • American buys Amer.Export Airlines then sells to Pan Am	in 1950. • American forms subsidiary Americana Hotels in 1963, and introduces SABRE, industry's first automated reservation system in 1964. • 1968 Smith (President), leaves to serve in Johnson Administration. • American buys Trans Caribbean Air in '71. • '77 Americana Hotels buys Howard Corp. Hotel properties, owns 21 hotels & resorts in US, Latin Am & Korea. Sold w/n 10 yrs.	• 1979 American moved its headquarters from NY to Dallas/Fort Worth.	• Former CFO Bob Crandall became president in 1980.	• American introduces industry's first frequent flyer program in 1981, using SABRE system to keep track of mileage.	• American created AMR Corporation as its holding company.				

of Airline Company over the Period of 1978 to 1994 (continued)

TABLE 4.5a

1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
		• Texas Air buys People Express Air and Frontier Air.		• Lorenzo sells Eastern's Air Shuttle to Donald Trump.	• Mounting losses and mechanist's strike forces Eastern into bankruptcy.	• Bankruptcy court removes Texas Air from Eastern's management. • Texas Air changes it's name to Continental Airlines Holdings. • Lorenzo resigns as chairman, president, and CEO after selling his stake in the company to SAS for a substantial premium plus $19.7 million in salary and severance pay. • Hollis L. Harris, former president of Delta Air is named CEO. • In late 1990, Continental follows Eastern into bankruptcy.	• Eastern is forced to liquidate due to mounting losses. • Harris leaves Continental and is replaced by former CFO Robert Ferguson. • Continental sells its Seattle-Tokyo route to AMR for $145 million.		• Out of bankruptcy in '93 Continental begins pursuing the short-haul market with a level of employee cooperation that would have been unthinkable in earlier years.	• Continental seeks to sell its Continental Express commuter airline.
			• the British government sold BA to the public • BA bought its chief British competitor, British Caledonian.	• BA gained a foothold in the US through a 1988 agreement with United Airlines and bought 11% of Covia Partnership, owner of United's Apollo computer reservation system. The two year old alliance with United ended when United gained service to Heathrow.		• BA negotiated with the Dutch carrier KLM to buy Belgium's Sabena World Airlines, but the deal collapsed.	• In 1991 it looked like BA and KLM would tie the knot, but in early 1992 an irresolvable dispute arose over how to value the two companies.	• Company acquired the principal European and domestic routes of Dan-Air.	• In '93, BA made a franchise deal with UK commuter airline CityFlyer Express, charging a fee for small airline to fly under BA's colors.	• Increase demand for luxury and business class seats lifted BA's revenues in '94. • Financial troubles of USAir pose a threat to BA's future profits and its plans to become a global airline.
			• 1987, AMR acquires Nashville Eagle commuter airline.	• AMR establishes AMR Eagle to operate commuter services as American Eagle, buying out 4 new commuter services in 1988 and 1989.	• AMR weathered an unsolicited takeover bid by Donald Trump and bought Eastern Air Line's Latin American routes form Texas Air.		• AMR bought TWA's US-London routes and won DOT approval to fly to Manchester, England. • AMR bought Continental's Seattle-Tokyo route and Midway Airline's gates at LaGuardia and Washington National airports.		• AMR asks flight attendants for concessions, resulting in a strike that took the airline into the red and tied up Thanksgiving weekend travel. • Strike ends when President Clinton persuaded the parties to go to arbitration.	• Attendant's pay and labor issues remain unsettled as of mid- 1994. • The airline has expressed an interest in exchanging equity for pay concessions, as archrival United did in 1994.

TABLE 4.5: Major Events of Airline Company over the P

TABLE 4.5b

Airlines	prior to 1978	1978	1979	1980	1981	1982	1983	1984	1985	1986	19[illegible]
Alaska Air Group	• In 1932 pilot Mac McGee started McGee Airways. • McGee joined other local operators to form Star Air Lines in 1937. • 1944, a year after buying three other airlines, Star adopted the name Alaska Airlines. • Alaska bought 2 more local carriers and established freight service to Africa and Australia, which resulted in losses that continued through the early 1970's. • Developer Bruce Kennedy led a boardroom revolt to gain control in '72, and turned Alaska around by '73.	• By '78 the airline served only 10 Alaskan cities and Seattle. • Civil Aeronautics Board forced Alaska to drop service to cities in northwestern Alaska, including Nome, in 1975.	• Kennedy became CEO in '79, shortly after the implementation of the '78 Airline Deregulation Act. • Deregulation allowed Alaska to exted operations into new areas like CA and to regain some of its lost routes including Nome.			• By '82, Alaska was the largest carrier operating between the US mainland and Alaska.	• After 40 years on the ASE, Alaska was listed on the NYSE.			• In '86, Alaska bought Long Beach-based Jet America Airlines (expanding its route network eastward to Chicago, St. Louis, and Dallas). • Alaska bought Seattle-based Horizon Air Industries (which served 30 cities in the Northwest.	[illegible]
KLM	• Albert Plesman founded KLM in The Hague in 1919. • KLM established service between Amsterdam and London,Copenhagen,Brussels, and Paris. • Initiated the longest air route in the world from Amsterdam to Indonesia in 1927 and extended network to Zurich, Rome,Prague, Vienna and Oslo. • Hitler's occupation of Holland shut down KLM's European operations. • By mid 50's, KLM expanded to Africa and Americas. • Company formed aerial photography and survey subsidiary, KLM Aerocarto	in '54. • In 1957, KLM's stock began trading on the NYSE. • Formed KLM Helikopters in 1965. • In 1966, established NLM Dutch Airlines, renaming it NLM CityHopper in '76.									[illegible]
Northwest Airlines	• A group of businessmen, led by Louis Brittin, founded Northwest Airways in 1926. • 1928, it became first US airline to offer coordinated airline and railroad service. • 1934, company changed it's name to Northwest Airlines, and expanded air routes to Seattle. • Service to NY completed the airline's transcontinental route in 1945. • Northwest started flying to the Far East in 1947, pioneering a Great Circle route to the Orient. • Donald Nyrop became Northwest's president in 1954. • Nyrop held debt to 10% of capital, the lowest proportion in airline industry.	• Nyrop retired in 1978, his successor, Joseph Lapensky, continued Nyrop's fiscal policies, keeping Northwest profitable throughout his tenure.						• Company formed NWA, a holding company.		• NWA bought Republic Airlines. • Northwest bought 50% of PARS (TWA's computer reservation system, which merged with Delta's DATAS II in 1190, forming WORLDSPAN). • Northwest's failure to reach an agreement with its unions after the Republic acquisition resulted in low employee morale.	

Events of Airline Company over the Period of 1978 to 1994 (continued)

TABLE 4.5b

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
on the s listed			• In '86, Alaska bought Long Beach-based Jet America Airlines (expanding its route network eastward to Chicago, St. Louis, and Dallas). • Alaska bought Seattle-based Horizon Air Industries (which served 30 cities in the Northwest.	• When competition in the east and midwest resulted in a 35% reduction in profits in '87, Kennedy shut down Jet America and concentrated on Alaska's and Horizon's operations along west coast.	• Airline opened service in 2 Mexican resorts in 1988		• High fuel prices and sluggish traffic crimped earnings for 1990, but Alaska Air managed to stay in the black.	• Kennedy retired as chairman in '91. • Alaska initiated service to Canada and seasonal flights to 2 Russian cities. • Formerly an Alaska Air Group partner, Neil Bert's MarkAir wages fare war, initiating new service in Alaska Air's territory. This cut into Alaska's profits and put MarkAir into bankruptcy.		• Despite smaller meals and more seats per plane, Alaska Air in '93 won recognition form Conde Nast Traveler magazine, which named it the best airline in the US for the 5th consecutive year.	
				• Sergio Orlandini, KLM president from '73 - '87, addressed the problems of overcapacity by converting rear portions of KLM's 747's to cargo space.	• In '88, company bought 40% of Transavia from Nedlloyd. • In '88 KLM bought 10% of Covia Partnership, owner and operator of United Air's Apollo computer reservation system.	• Invested in Wings Holdings, a company established to buy Northwest Airlines in 1989	• A deal giving KLM and British Airways 20% of each of Belgium's national airline, Sabena, fell apart in 1990.	• KLM raised its stake in Transavia to 80% and bought 35% of Air Littoral and 40% of ALM Antillean Airlines. • KLM sold a 49% interest in KLM Helicopters (renamed KLM ERA Helicopters) to Houston-based ROWAN Companies. • In 1990, it looked as though KLM and British Airways would unite, but by early 1992, talks had collapsed.	• KLM tied up an agreement with Northwest Airlines in 1992 to share operations, but KLM was hurt by Northwest's large losses in 1992.		• Following Northwest's return to profitability, KLM bought up brewer Foster's 5-6% stake in the airline in 1994 for $180 million, bringing it's ownership in Northwest to nearly 25%.
	• Company formed NWA, a holding company.		• NWA bought Republic Airlines. • Northwest bought 50% of PARS (TWA's computer reservation system, which merged with Delta's DATAS II in 1990, forming WORLDSPAN). • Northwest's failure to reach an agreement with its unions after the Republic acquisition resulted in low employee morale.			• Northwest's pilots still had no contract in 1989 when Wings Holdings - an investment group that included KLM and was led by former Marriott executive Alfred Checchi- took NWA private in a $3.65 billion LBO, after which Checchi became chairman.	• NWA bought a 25% stake in Hawaiian Airlines gaining 3 Pacific routes. • The high fuel prices and decreased travel due to Iraq's invasion of Kuwait produced huge losses for NWA in 1990 and 1991.	• In 1991 Northwest needed dmoney and persuaded Minnesota to back a new bond issue. • In 1991 it bought Eastern's Washington, DC landing slots and arranged $20 million in debtor-in-possession financing for America West, gaining the option to buy the ailing Phoenix-based carrier's route from Honolulu to Nagoya, Japan. • After paying $20 million for Midway Airline's 21 gates and other facilities at Chicago's Midway's Airport, NWA backed out of a broader deal to buy the bankrupt Chicago-based carrier.	• NWA sold 18 of its Midway Airport gates and other assets to Southwest Airlines for $15 million in 1992. • NWA released its interest in Hawaiian Airlines.	• In 1993, it initialized service to Raleigh/Durham, NC, Greenville/Spartanburg SC, and Reno, as part of its strategy of expanding by assuming low-traffic routes and allying with smaller airlines to act as feeders into its hubs. • After the IPO, NWA renamed itself Northwest Airlines Corp. and kept searching for ways to save or raise money. • Cancellation of plane orders left the airline with a fleet that averages 5 years older than industry averages.	• In 1994, it mortgaged 10 planes in a $243 million note offering.

TABLE 4.5: Major Events of Airline Company over the Period

TABLE 4.5c

Airlines	prior to 1978	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
Southwest Airlines	• Rollin King and Herb Kelleher founded Air Southwest Company in 1967. • Braniff and Texas Intl. sued SW but TX Supreme court ruled in SW favor. • 71, renamed to Southwest Airlines, made its first scheduled flight. • To curb maintenance costs, SW uses only fuele efficient Boeing 737's. • 74 SW stays at Love Field TX gaining virtual monopoly at the airfield. • Wright Amendment in 79 prevents airlines operating out of Love Field from providing direct service to states other than those neighboring TX.	• Lamar Muse, Southwest president resigned in 78 due to differences with King. • Kelleher became president. • Muse took over son's Muse Air Corp. and in 85 sold to SW. Kelleher operated this Houston-based airline, but liquidated it in 1987.								• Kelleher introduced advance-purchase "Fun Fares" in 1986.	• Fre base fligh mile in 19
United Airlines UAL Corporation	• Bill Boeing and Fred Rentschler merged their co.'s (Boeing Airplane/Pratt & Whitney) to form United Aircraft and Transport in 1929. • Renamed to United Air Lines in 1931, NY-based co. offered one of US first coast to coast airline services. • 1934, manufac. and transport. divisions split, and Bill Patterson becomes president of the latter (UA) moving it to Chicago. • 1961, UA became U.S.'s #1 airline after buying Capital Air. • Bought Westin Hotel Co. in 1970. • Named Westin president Eddie Carlson as United's CEO in 1970.		• Richard Ferris became CEO in 1979.						• Ferris spent $2.3 billion buying Hertz Corp ('85), Pan Am's Australian and Asian routes ('86), Transworld's Hilton Intl. ('87).		• Aft millio name Ferris Conn comp share to use liquid • Asn under UA s car re well a comp partne
Delta Air Lines, Inc.	• Was founded in Macon, GA in 1924, as Huff-Daland Dusters. • Moved to Monroe, LA in 1925. • 1928-C.E. Woolman and 2 partners bought the service and renamed it Delta Air Service. • 1929-Delta pioneered passenger service, operating without a govt. mail subsidy until 1934. • Delta moved to Atlanta in 1941. Woolman became president in 1945 and ran Delta until he died in 1966. • 1952 purchase of Chicago and Southern Airlines made Delta the 5th largest US airline. • 1972 Delta bought Northeast Airlines.					• Delta's employees pledged $30 million to buy a Boeing 767 jet.	• In fiscal 1983, Delta succumbed to the weak US economy, posting its first loss ever.			• Profitable again in '85. Delta bought Los Angeles based Western Air Lines in 1986.	• Delt Asia i

Events of Airline Company over the Period of 1978 to 1994 (continued)

TABLE 4.5c

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
			• Kelleher introduced advance-purchase "Fun Fares" in 1986.	• Frequent-flyer plan based on the number of flights rather than mileage is introduced in 1987.	• SW became official airline of Seaworld (TX), as Kelleher painted a 737 to resemble Shamu.		• SW established an operating base at Phoenix Sky Harbor Airport in 1990. • Airline continues to add destinations, Oakland and Indianapolis ('89), Burbank and Reno('90), Sacramento ('91), San Jose ('93), and Spokane ('94).		• SW assumed the lease operations of Northwest Airlines at Chicago Midway Airport and Detroit Metro. Airport. • Airline wins its first annual Triple Crown for the best on-time performances, best baggage handled, and best customer satisfaction in 1992 and repeated in 1993.	• Initiated service to Baltimore, its first East Coast destination.	
		• Ferris spent $2.3 billion buying Hertz Corp ('85), Pan Am's Australian and Asian routes ('86), Transworld's Hilton Intl. ('87).		• After spending $7.3 million to change United's name to Allegis Corp. Ferris resigned when Coniston Partners, the company's largest shareholder, threatened to oust the board and liquidate the company. • Assuming its old name under Stephen Wolf, UA sold its hotels and car rental business as well as 50% of its computer reservation partnership (Covia).		• A takeover bid by LA billionaire Marvin Davis led to a management and union buyout plan, which failed in 1989.	• A second union buyout plan, fails in 1990. • United then reached an accord with Coniston, which sold most of its stake in UAL in exchange for 2 seats on the board. • United received DOT permission to fly from Chicago to Tokyo.	• In 1991 and 1992 UA bought Pan Am's London and Paris routes, most of Pan Am's Latin America routes, and it's LA-Mexico City route.	• UA bought Air Wisconsin in 1992.	• UA sought to negotiate a buyout with its unions. Early in the year it cancelled plans to hire 1900, instead laying off 2800 and cutting management salaries and director's fees. • The sale of UA's kitchen operations to Dial's Dobbs Houses and the announcement of plans to start up a subsidiary short-haul airline brought the pilots and machinists back to the table.	
iscal 1983, Delta umbed to the weak conomy, posting its loss ever.			• Profitable again in '85. Delta bought Los Angeles based Western Air Lines in 1986.	• Delta began service to Asia in 1987.		• By 1989 international routes provided 11% of the co.'s revenues. • Delta signed agreements with Swissair and Singapore Air, allowing the 3 airlines to buy stakes of up to 5% in one another.	• Delta joined TWA and Northwest to form WORLDSPAN, a computer reservation service. • Fare discounts and higher fuel and labor costs reduced earnings by 34%, despite a 6% growth in sales.	• Delta bought gates, planes, and 3 Canadian routes from Eastern and Pan Am's NY to Boston shuttle, and Frankfurt hub, for $621 million in cash and $668 million in debt assumption. • This made Delta the world's largest airline, in terms of cities served and profitability. • However, due to the economy, and fare wars, Delta posted its first loss since 1983.	• After suffering a larger loss in '92, Delta began several rounds of cost cutting. • Pan Am and some of its creditors filed a $2.5 billion breach of contract lawsuit against the company after Delta backed out of an agreement to fund Pan Am's reorganization.	• Delta was cutting costs by laying off permanent workers, delaying orders for planes, retiring aircraft, and signing joint venture agreements such as Virgin Atlantic and Australian Airlines to help reduce costs on international routes.	

TABLE 4.5: Major Events of Airline Company over th

TABLE 4.5d

Airlines	prior to 1978	1978	1979	1980	1981	1982	1983	1984	1985	1986
USAir Group, Inc.	• 1937- Richard Cole Pont founded All American Aviation. • All American picked up and delivered mail: passenger service commenced in 1949. • The company renamed Allegheny Airlines in 1953. • Allegheny Commuters (now USAir Express) began offering commuter links with Allegheny's route system in 1967. • Airline gained routes in the Great Lakes area, New Yore, and the East Coast by buying Lake Central Airlines (1968), and Mohawk Airlines in (1972).	• Company president Edwin Colodny became chairman in 1978. • In 1979 Colodny renamed airline to USAir.							• USAir augmented its commuter service by buying Pennsylvania Commuter Airlines (1985) and Suburban Airlines in (1986).	
Trans World Airlines, Inc.	• Was founded as Wetern Air Express by Harry Chandler and James Talbot in 1925. • It merged with Transcontinental Air Transport in 1930 to form Transcontinental and Western Air, America's first coast to coast airline • Howard Hughes bought TWA in 1939, it introduced transatlantic service in 1946, moved its headquarters in NY in 1947, and changed its name to Trans World Airlines in 1950. • 1956 - Hughes ordered 63 jets with long term financing through a NY investment banker. When he was unable to meet the terms of the loan in 1960, the bank placed Hughe's TWA stock in a voting trust. Hughes then sold his interest	to the public in 1966.	• TWA tried to stabilize earnings through acquisitions (consolidated under Trans World Corp. in 1979). These included Hilton Int. (hotels, 1967), CAnteen Corp.(food services, 1973), Spartan Food Systems (Hardee's restaurants, 1979) and Century 21 (real estate, 1979).					• In 1984 TWA's problems led to a split from Trans World Corp., which becames TW Services in 1986 after selling its hotels to United Air Lines		• In 1986, over TWA a takeover Frank Lo

Events of Airline Company over the Period of 1978 to 1994 (continued)

TABLE 4.5d

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
		• USAir augmented its commuter service by buying Pennsylvania Commuter Airlines (1985) and Suburban Airlines in (1986).		• After rebuffing a takeover bid by TWA in 87, USAir acquired Piedmont Aviation and Los Angeles-based Pacific Southwest Airlines.	• In 1988 USAir bought 11% of Covia Partnership. • Covia merged with the European CRS operator Galileo in 1992, forming Galileo Intl. of which USAir owns 11%.	• USAir offered its first transatlantic flight in 1989. • Difficulty in integrating USAir and Piedmont (one of the largest airline mergers in history), combined with the rising cost of jet fuel, resulted in USAir's only loss during the 1980's and ended 12 consecutive years of profitability.	• As losses continued into 1990 and 1991, the company cut jobs and sold its engine maintenance and general aviation units.	• Colodny retired in 1991 leaving Seth Schofield in charge. • USAir spent $50 million in 1991 for TWA's London routes and $16.2 million in 1992 for a 40% equity stake (and an option to buy) in the Trump Shuttle.	• Losses continued in '92 with a 5 day long mechanic's strike, which stranded passengers, and the construction of new terminals at LaGuardia and Pittsburgh.	• Later in 1993, USAir initiated Philadelphia-Frankfurt service.	• As the airline has aged, it has found itself hard pressed to compete with lower-cost competitors like Continental's new CALite services. • In 1994, with losses still mounting, a management shakeup began when president and chief of operations Michael Schwab resigned after receiving criticism form unions. He was replaced by CFO Frank Salizzoni. • In 1994, under pressure from director Warren Buffett, USAir's ground crews voted to unionize.
	• In 1984 TWA's problems led to a split from Trans World Corp., which becomes TW Services in 1986 after selling its hotels to United Air Lines		• In 1986, Carl Icahn took over TWA after winning a takeover battle with Frank Lorenzo.	• Icahn, as CEO, bought Ozark Air Lines (TWA's main competitor at its St. Louis hub) in 1987.	• By 1988, when he took TWA private (recouping his $356 million investment), Icahn owned 90% of TWA, with the other 10% owned by its employees.		• TWA, Delta, and NWA formed the computer reservation system WORLDSPAN in 1990. • Late in 1990 Icahn proposed merging TWA with financially beleaguered Pan Am. Talkes failed when Pan Am sold its London routes to United. Fearing transatlantic competition from United, TWA agreed to sell its London routes (to Heathrow Airport) to American Airlines, planning to use proceeds to buy Pan Am, which then entered bankruptcy.	• Delta outbid TWA for Pan Am in 1991.	• After filing for bankruptcy protection itself in 1992, TWA sold most of its television subsidiary (The Travel Channel); it also sold routes from Philadelphia and Baltimore to London's Gatwick Airport to USAir. • TWA's attempt to open a hub in Atlanta in 1992 failed because it lacked the fleet to compete in that busy market.	• In 1993 TWA moved its headquarters to St. Louis, the location of its largest hub, and in 1994 the airline further reduced its network by reducing service in the Northeast and cutting back service to Europe.	

TABLE 4.6: Sales Volume over the Period of 1984 to 1992

Unit= USD MIL

	1984	1985	1986	1987	1988	1989	1990	1991	1992	AVG
American airlines	5,354	6,131	6,018	7,198	8,824	10,480	11,720	12,887	14,396	9,223
United Airlines	6,218	5,306	7,119	8,305	8,982	9,794	11,037	11,663	12,890	9,035
Delta Airlines	4,264	4,684	4,460	5,318	6,915	8,089	8,582	9,171	10,837	6,924
British Airways PLC	-	2,036	4,511	5,245	7,091	7,184	7,971	8,632	9,069	5,749
Northwest	2,445	2,655	3,589	5,142	5,650	6,576	7,426	7,683	8,128	5,477
Continental Airlines, Inc.	1,372	1,944	4,407	8,626	8,552	6,650	6,184	5,487	5,494	5,413
US Air	1,630	1,765	1,835	3,001	5,707	6,252	6,559	6,514	6,686	4,439
Trans World Airlines	3,657	3,867	3,185	4,056	4,361	4,507	4,606	3,660	3,634	3,948
KLM	1,618	2,310	2,637	3,002	2,792	3,386	3,426	4,290	4,549	3,112
Southwest Airlines	536	680	769	778	860	1,058	1,237	1,379	1,803	1,011
Alaska Airlines	362	433	468	710	814	917	1,047	1,104	1,115	774

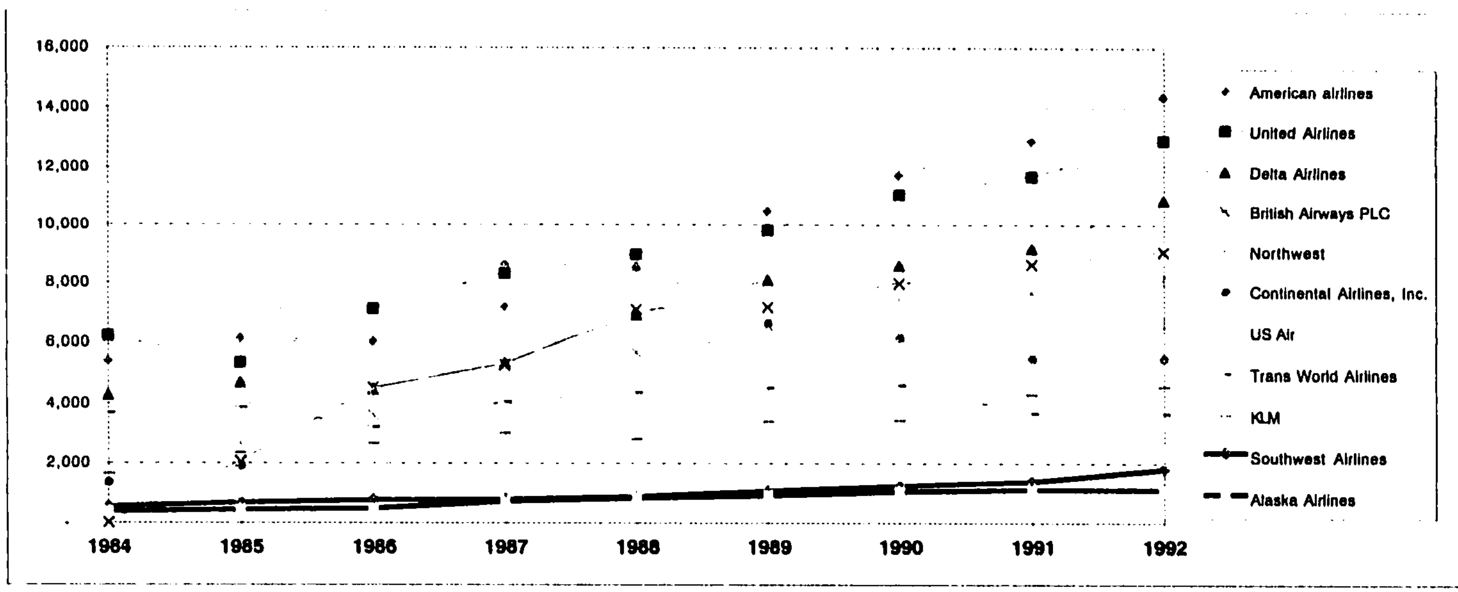


TABLE 4.7: Net Income over the Period of 1984 to 1992

Unit= USD MIL

	1984	1985	1986	1987	1988	1989	1990	1991	1992	AVG
British Airways PLC		120	280	238	285	295	405	166	443	279
American airlines	234	346	279	198	477	455	(40)	(240)	(475)	137
Southwest Airlines	50	47	50	20	58	75	51	33	97	53
Delta Airlines	176	259	47	264	307	461	303	(324)	(506)	110
United Airlines	282	(49)	12	(4)	600	324	94	(332)	(417)	57
KLM	84	122	148	169	175	178	(330)	68	(311)	34
Alaska Airlines	24	26	18	13	37	43	17	10	(80)	12
US Air	122	117	98	195	165	(63)	(454)	(305)	(601)	(81)
Trans World Airlines	30	(208)	(106)	45	250	(287)	(274)	(11)	(318)	(98)
Northwest	56	73	77	103	135	75	(465)	(488)	(1,482)	(213)
Continental Airlines, Inc.	28	49	42	(466)	(719)	(908)	(2,403)	(306)	(125)	(534)

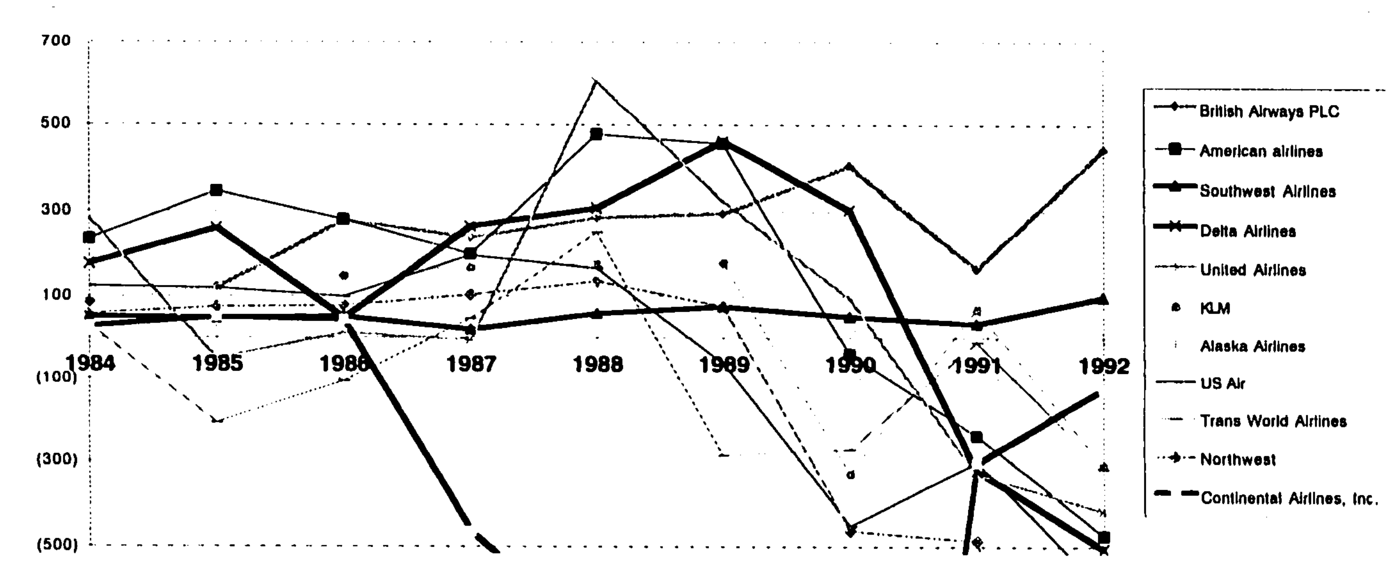


TABLE 4.8: Net Income as % of Sale over the Period of 1984 to 1992

Net Income as % of sale = Net Income/Sale

	1984	1985	1986	1987	1988	1989	1990	1991	1992	AVG
Southwest Airlines	9.3%	6.9%	6.5%	2.6%	6.7%	7.1%	4.1%	2.4%	5.4%	5.7%
British Airways PLC		5.9%	6.2%	4.5%	4.0%	4.1%	5.1%	1.9%	4.9%	4.6%
Alaska Airlines	6.6%	6.0%	3.8%	1.9%	4.6%	4.7%	1.6%	0.9%	-7.2%	2.5%
American airlines	4.4%	5.6%	4.6%	2.8%	5.4%	4.3%	-0.3%	-1.9%	-3.3%	2.4%
Delta Airlines	4.1%	5.5%	1.1%	5.0%	4.4%	5.7%	3.5%	-3.5%	-4.7%	2.3%
KLM	5.2%	5.3%	5.6%	5.6%	6.3%	5.3%	-9.6%	1.6%	-6.8%	2.0%
United Airlines	4.5%	-0.9%	0.2%	0.0%	6.7%	3.3%	0.9%	-2.8%	-3.2%	0.9%
US Air	7.5%	6.6%	5.4%	6.5%	2.9%	-1.0%	-6.9%	-4.7%	-9.0%	0.8%
Northwest	2.3%	2.7%	2.1%	2.0%	2.4%	1.1%	-6.3%	-6.4%	-18.2%	-2.0%
Trans World Airlines	0.8%	-5.4%	-3.3%	1.1%	5.7%	-6.4%	-5.9%	-0.3%	-8.8%	-2.5%
Continental Airlines, Inc.	2.0%	2.5%	1.0%	-5.4%	-8.4%	-13.7%	-38.9%	-5.6%	-2.3%	-7.6%

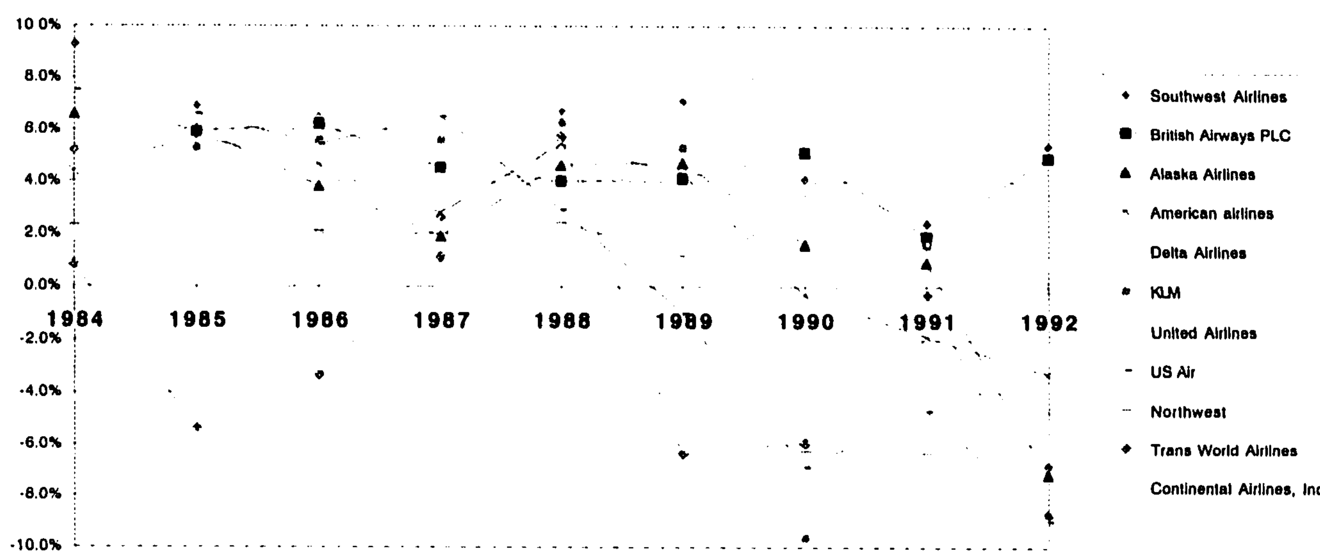


TABLE 4.9: Summary Correlation Coefficients for Relative Closeness

- From the Perspective of American Airlines -

	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	AVG
AIRCAL									-0.0420							-0.0210
ALASKA	0.0667			0.4717	0.0686	0.4142	0.3264	0.1792	0.0681	0.2210	0.1913	0.3183	0.1516	0.1245	0.1319	0.2135
ALOHA			-0.1613	0.2155	0.2477	0.1759	0.1512	-0.1374	0.2764							0.1111
BRITISH											0.2767	-0.3479	0.2477	-0.0060	-0.0072	0.0327
CONT	0.4832	0.3756	0.5362	0.2563	-0.1736	0.3686	0.2931	0.2355	-0.0745	0.3856	0.2946	0.3337	0.0117	-0.0750		0.2324
DELTA	0.4207	0.4271	0.4443	0.4776	0.6823	0.6626	0.7050	0.6329	0.6026	0.5334	0.5996	0.5237	0.7729	0.6010	0.7178	0.5789
EASTERN	0.5031		0.5330	0.6949	0.4034	0.3688	0.2276	0.3918								0.4461
FRONTIER	0.4156	0.2462	0.3213	0.4737	0.2671	0.2550	0.2764									0.3222
HAWAIIAN	0.4490		0.2462	0.0296	0.0175	0.2004	-0.0962	-0.2272	0.1133					-0.1641		0.0632
KLM		0.3244		0.1804	0.2791	0.1944	0.1116	0.3551	0.1656	0.2796	-0.0133	-0.0555	0.2727	0.0299	0.1752	0.1764
NW	0.4642	0.4350	0.4813	0.6021	0.5076	0.7233	0.6476	0.2847	0.6284	0.4366	0.4409					0.5107
PAN AM	0.3094		0.3345	0.3531	0.2619	0.3941	0.4471	0.2116	0.1709	-0.0079	0.1674	0.2663	-0.0427			0.2406
PIEDMONT		0.1757	0.1174	0.3646	0.2353	0.3306	0.4387	0.4542	0.4169							0.3192
REPUBLIC	0.2103	0.5812	0.3014	0.4302	0.0583	0.2706	0.4450	0.5276								0.3531
SOUTHWEST	0.1020	0.0225	0.1807	0.2660	0.3930	0.4667	0.5196	0.3710	0.0636	0.4576	0.3904	0.2533	0.1967	0.4366	0.3662	0.3019
TIGER	0.1813	0.3327	0.4025	0.2580	0.0506	0.3243	0.2178	0.2546	-0.1232	0.0324	0.0825					0.1630
TWC	0.5379	0.2551	0.5176	0.5621	0.5950	0.5481	0.5570	0.1541	0.2624	-0.0315						0.3978
UNITED	0.5062	0.5489	0.7400	0.7084	0.3906	0.7683	0.6844	0.6405	0.7280	0.1496	0.4929	0.4710	0.2328	0.7025	0.7296	0.5669
USAIR	0.2290	0.3645	0.5604	0.5929	0.5471	0.7977	0.5616	0.0879	0.5036	0.4015	0.2669	0.1796	0.3155	0.4049	0.3937	0.4178
WORLDCORP	0.3710		0.2975	0.3367	0.1224	0.2913	0.1026	0.1661	0.0940	-0.0076	-0.0327	-0.0379	-0.0179	-0.1066	0.0975	0.1197
MAX	0.5379	0.5812	0.7400	0.7084	0.6823	0.7977	0.7050	0.6405	0.7280	0.5334	0.5996	0.5237	0.7729	0.7025	0.7296	0.5789
MIN	0.0667	0.0225	0.1613	0.0296	-0.1736	0.1759	-0.0962	-0.2272	-0.1232	-0.0315	-0.0327	-0.3479	-0.0427	-0.1641	-0.0072	0.0327
MEAN	0.3506	0.3422	0.3677	0.4070	0.2763	0.4218	0.3865	0.2684	0.2610	0.2374	0.2687	0.1007	0.2141	0.1848	0.3268	0.2941
STD	0.1473	0.1465	0.2056	0.1603	0.2173	0.1966	0.2172	0.2282	0.2519	0.1976	0.1692	0.2526	0.2219	0.2660	0.2613	0.1590

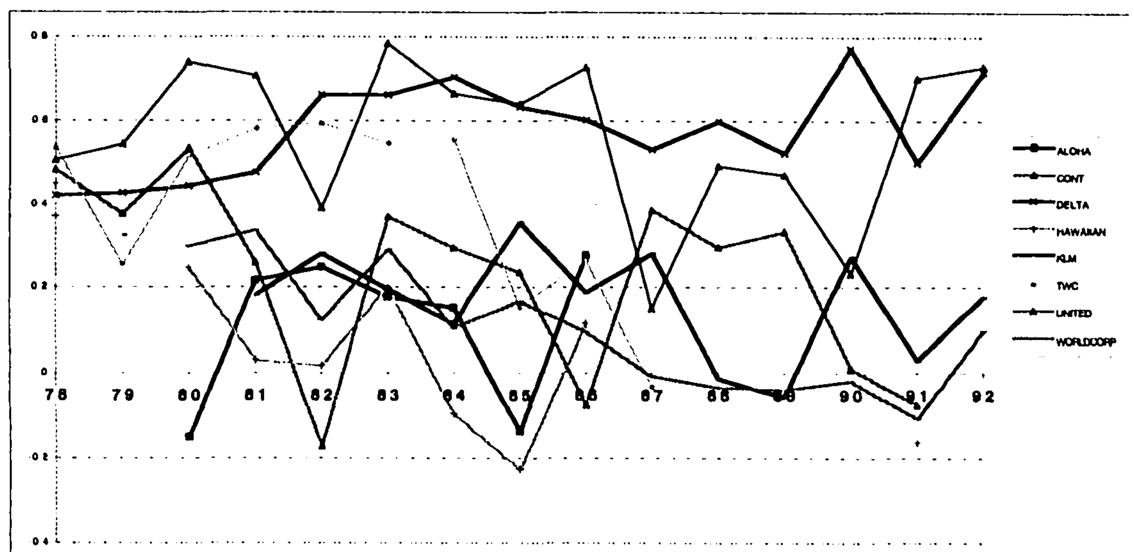
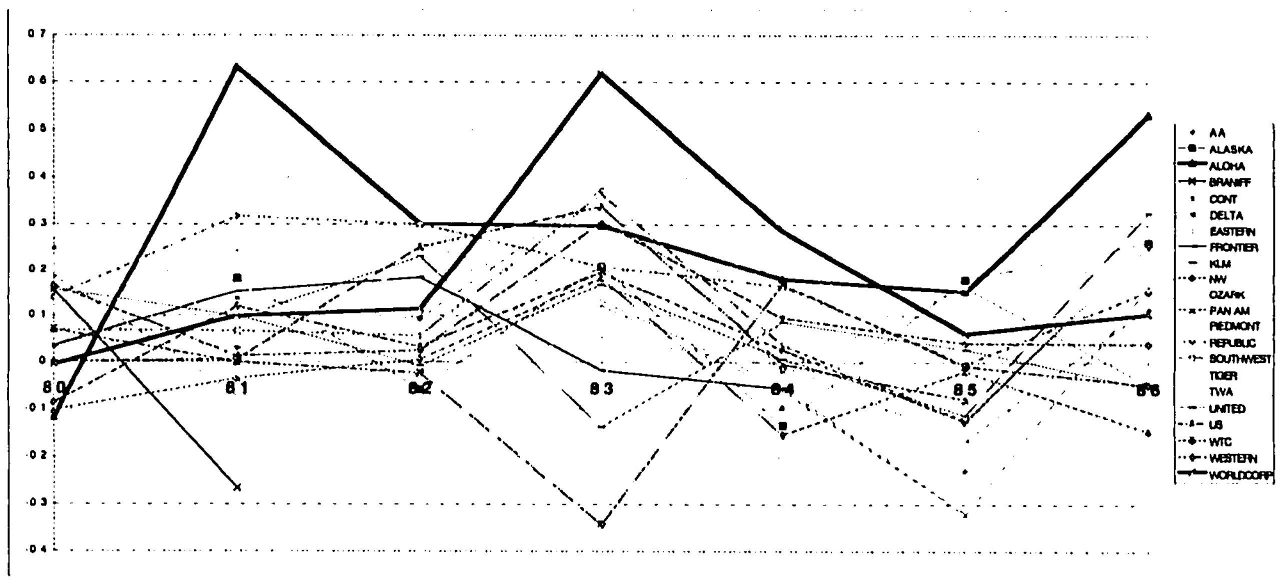


TABLE 4.10: Summary Correlation Coefficients for Relative Closeness - From the Perspective of Hawaiian Airlines -

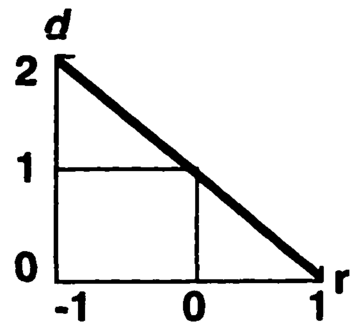
	80	81	82	83	84	85	86	Grand Summary
AA	0.2462	0.0296	0.0175	0.2004	-0.0962	-0.2272	0.1133	0.0405
ALASKA		0.1802	-0.0591	0.2081	-0.1344	0.179	0.2612	0.1058
ALOHA	**-0.1172**	**0.6318**	**0.3009**	**0.2966**	**0.1809**	**0.1528**	**0.5328**	**0.2827**
BRANIFF	0.1542	-0.2668						(0.0563)
CONT	0.0483	0.0325	0.0986	0.1221	-0.0605	-0.3218	0.1622	0.0116
DELTA	0.0332	0.1382	0.0928	0.3758	-0.0159	0.1623	-0.0465	0.1057
EASTERN	0.1202	0.2425	0.2595	0.1332	-0.0524	-0.3194		0.0639
FRONTIER	0.0338	0.1515	0.1842	-0.0184	-0.0563			0.0590
KLM		0.0911	0.2303	-0.1373	0.0847	0.0278	-0.0541	0.0404
NW	-0.0882	0.1192	0.0328	0.1948	0.0255	-0.1262	0.2544	0.0589
OZARK	0.2239	0.096	0.197	0.1629	0.2299	0.0089		0.1531
PAN AM	-0.1025	-0.0351	0.0057	0.1616	-0.1528	-0.0197	-0.1455	(0.0363)
PIEDMONT	0.2026	0.0056	0.1594	0.3211	0.0052	-0.0158	0.1719	0.1214
REPUBLIC	0.0667	0.066	0.0563	0.3651	0.0376	-0.1237		0.0780
SOUTHWEST	0.1396	0.3176	0.2999	0.2077	0.1648	-0.0039	0.1528	0.1826
TIGER	0.2824	0.1694	-0.0419	-0.027	0.2322	-0.0541	-0.0507	0.0729
TWA	0.1866	-0.0731	-0.0043	0.054	-0.0063	-0.1659	0.1171	0.0154
UNITED	0.1568	0.0985	-0.0089	0.1667	0.007	-0.1119	0.3255	0.0908
US	0.165	0.0128	0.0242	0.3044	0.0948	0.0414	0.0394	0.0974
WTC	0.0686	-0.0015	-0.023	-0.344	0.1687	-0.0085	-0.0485	(0.0269)
WESTERN	-0.0005	0.006	0.2507	0.3387	-0.0045	-0.0801		0.0851
WORLDCORP	-0.0048	0.098	0.1149	0.6182	0.2846	0.0615	0.1039	0.1623
MAX	0.2824	0.6318	0.3009	0.6182	0.2846	0.1790	0.5328	0.2827
MIN	-0.1172	-0.2668	-0.0591	-0.3440	-0.1528	-0.3218	-0.1455	-0.0563
MEAN	0.0826	0.0991	0.1085	0.1763	0.0516	-0.0378	0.1184	0.0803
STD	0.1104	0.1677	0.1159	0.2024	0.1209	0.1353	0.1730	0.0776



Exhibits

EXHIBIT 2.1: Linear Transformations

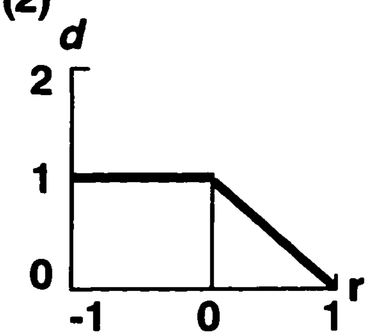
(1)



**Closeness:
Strength of association
and direction**

**Cooperative strategic
interactions**

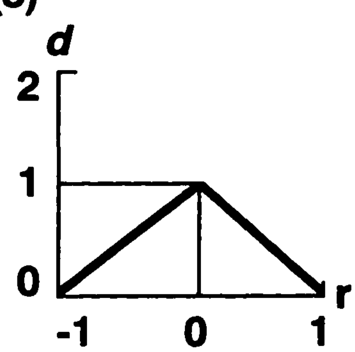
(2)



**Closeness:
Strength of association
and direction, but only
positive side**

In the middle

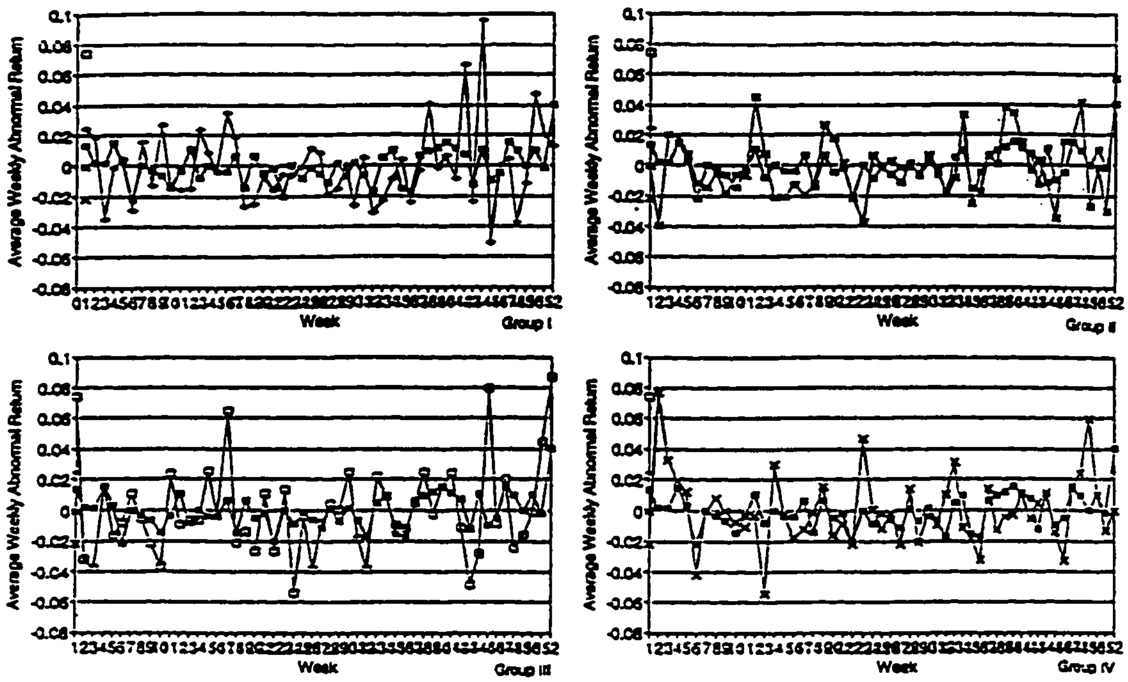
(3)



**Closeness:
Strength of association
Sign doesn't matter**

**Non-cooperative strategic
interactions**

EXHIBIT 2.2: Average Weekly Abnormal Return (4 Groups)



Note that the average weekly abnormal return is defined as the average of residuals from the market regression model after adjusting for stock split and dividend payment (see 4.3.1 for detail).

	Total	G1	G2	G3	G4
avg	0.00000	(0.00000)	0.00000	(0.00000)	0.00000
std	0.01133	0.02635	0.02154	0.03074	0.02349

Exhibit 2.3: Niche Presence of 4 Groups

Cluster I

	MFG.	MKTS.	DIST.	R&D	LEASE	OTHER	
COMPONENTS	5	4	1	2	0	0	12%
POWER	1	0	0	1	0	0	2%
INDUSTRIAL	2	1	0	2	0	0	6%
INSTRUMENTS	8	7	1	6	0	0	23%
CUMMUNICATIONS	2	2	2	2	0	0	10%
CONSUMER	4	4	0	2	0	0	10%
COMPUTERS	4	4	0	4	0	0	11%
GOVERNMENT	0	0	0	0	0	0	0%
TRANSPORTATION	4	2	1	4	0	0	11%
NON-ELEC	5	6	2	2	0	0	15%
	35%	30%	8%	26%	0%	0%	

Cluster II

	MFG.	MKTS.	DIST.	R&D	LEASE	OTHER	
COMPONENTS	10	6	0	6	0	0	21%
POWER	2	0	0	1	0	0	3%
INDUSTRIAL	5	2	1	2	0	0	10%
INSTRUMENTS	8	3	1	5	0	0	17%
CUMMUNICATIONS	4	2	0	2	0	0	8%
CONSUMER	5	4	2	2	1	0	13%
COMPUTERS	6	6	1	3	1	0	17%
GOVERNMENT	0	0	0	0	0	0	0%
TRANSPORTATION	2	2	1	0	0	0	4%
NON-ELEC	2	2	0	2	0	1	7%
	44%	28%	5%	21%	2%	1%	

Cluster III

	MFG.	MKTS.	DIST.	R&D	LEASE	OTHER	
COMPONENTS	6	3	1	3	0	0	13%
POWER	1	0	0	0	0	0	1%
INDUSTRIAL	6	6	2	5	0	0	19%
INSTRUMENTS	4	3	2	4	0	0	13%
CUMMUNICATIONS	5	2	1	3	1	0	12%
CONSUMER	4	3	1	2	1	0	11%
COMPUTERS	7	5	0	6	0	0	18%
GOVERNMENT	1	0	0	1	0	0	2%
TRANSPORTATION	1	0	0	1	0	0	2%
NON-ELEC	3	3	0	2	0	0	8%
	38%	25%	7%	27%	2%	0%	

Cluster IV

	MFG.	MKTS.	DIST.	R&D	LEASE	OTHER	
COMPONENTS	8	8	1	7	0	1	27%
POWER	1	0	1	1	0	0	4%
INDUSTRIAL	0	0	0	0	0	0	0%
INSTRUMENTS	5	4	2	2	0	0	13%
CUMMUNICATIONS	4	2	1	2	0	0	10%
CONSUMER	0	0	1	1	0	0	2%
COMPUTERS	11	10	5	8	0	0	34%
GOVERNMENT	1	0	0	1	0	0	2%
TRANSPORTATION	0	0	0	0	0	0	0%
NON-ELEC	2	2	2	1	0	0	8%
	33%	27%	14%	25%	0%	1%	

Note that the numbers in the cells are percent (i.e. 3 percent if there are 3 niche presences among 100 possible niche presences in a group).

Exhibit 2.4: Plot of CAN1 and CAN2

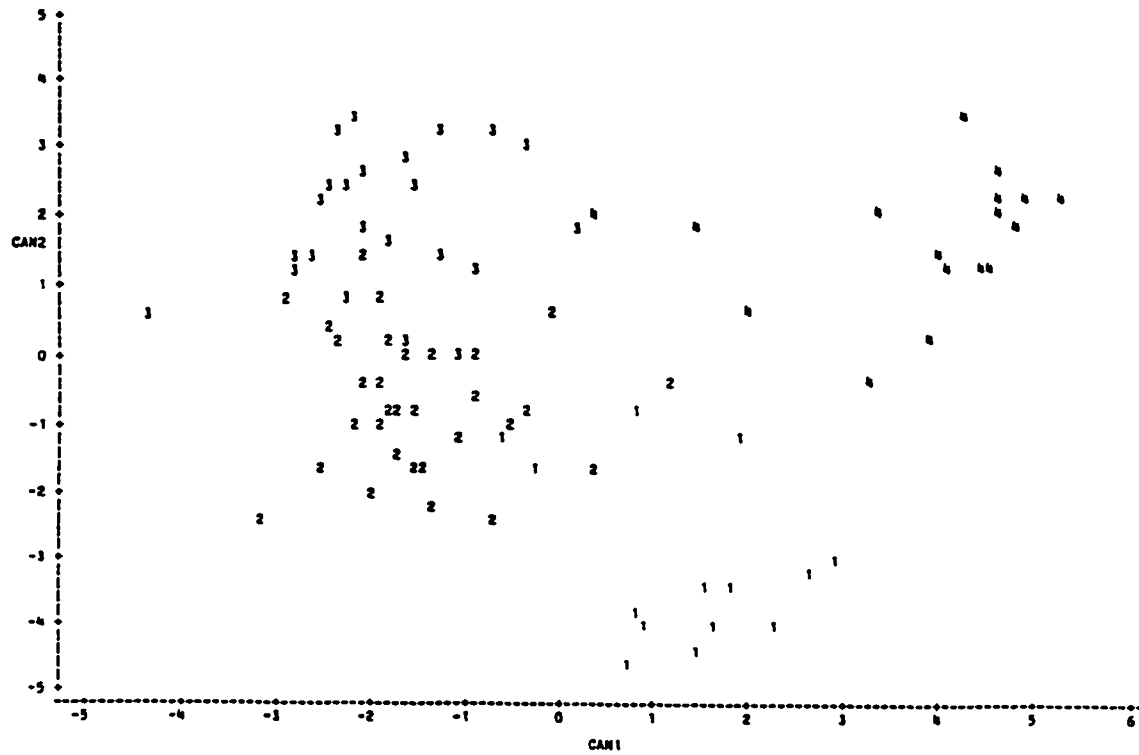
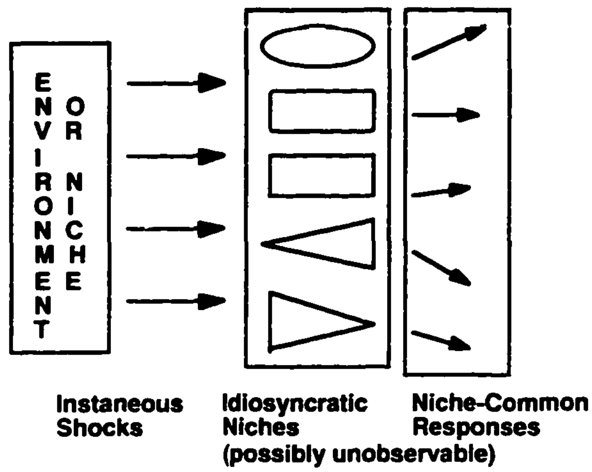


EXHIBIT 3.1: Diagram for the Stock Return Method

Assume that niche idiosyncrasies are given and stable.



If there is any spontaneous disturbances from outside firms, the spot responses of firms across the existing niches will be different up to the point where they are fundamentally different.

EXHIBIT 3.2: Plot of 1st and 2nd Principal Components

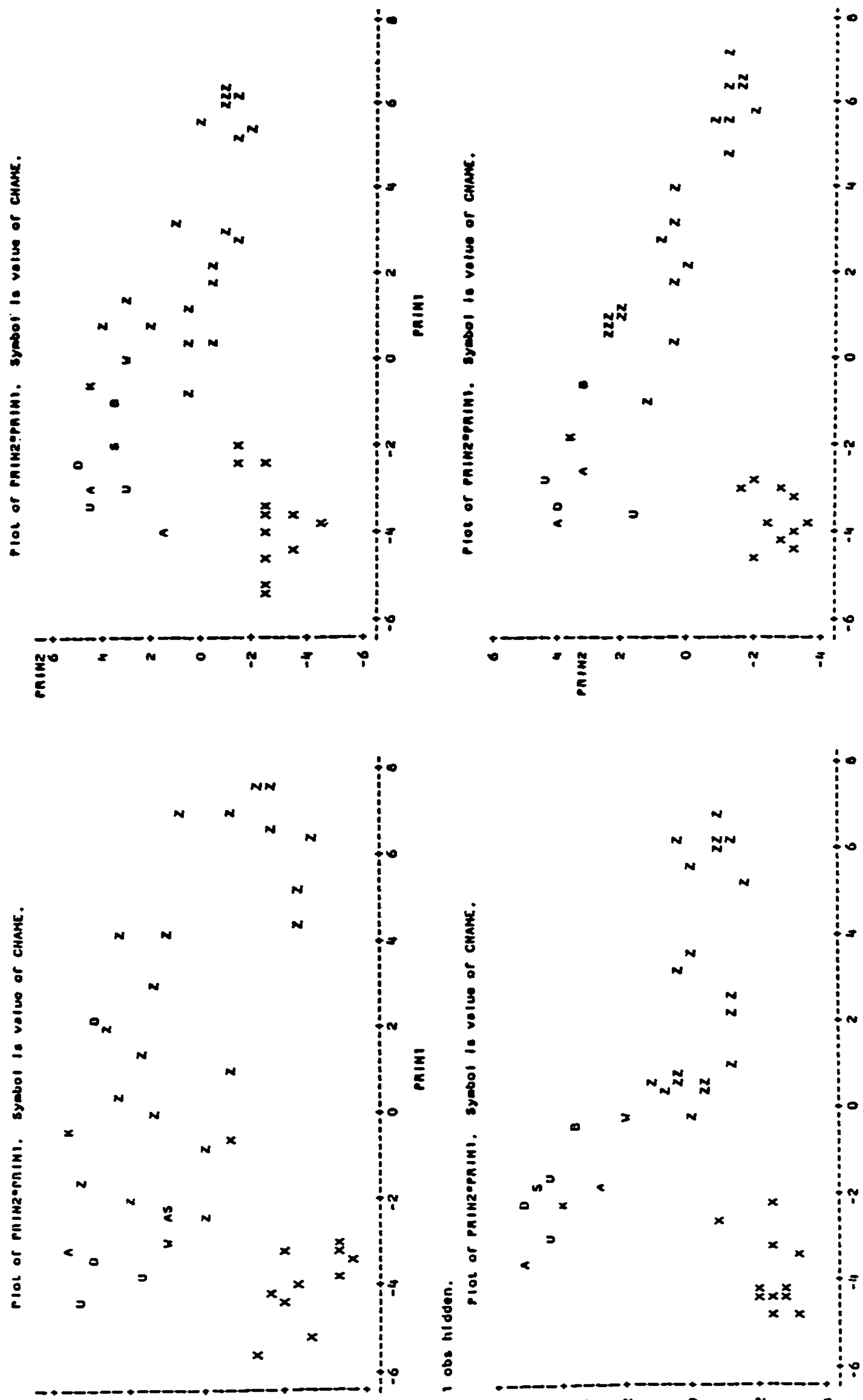
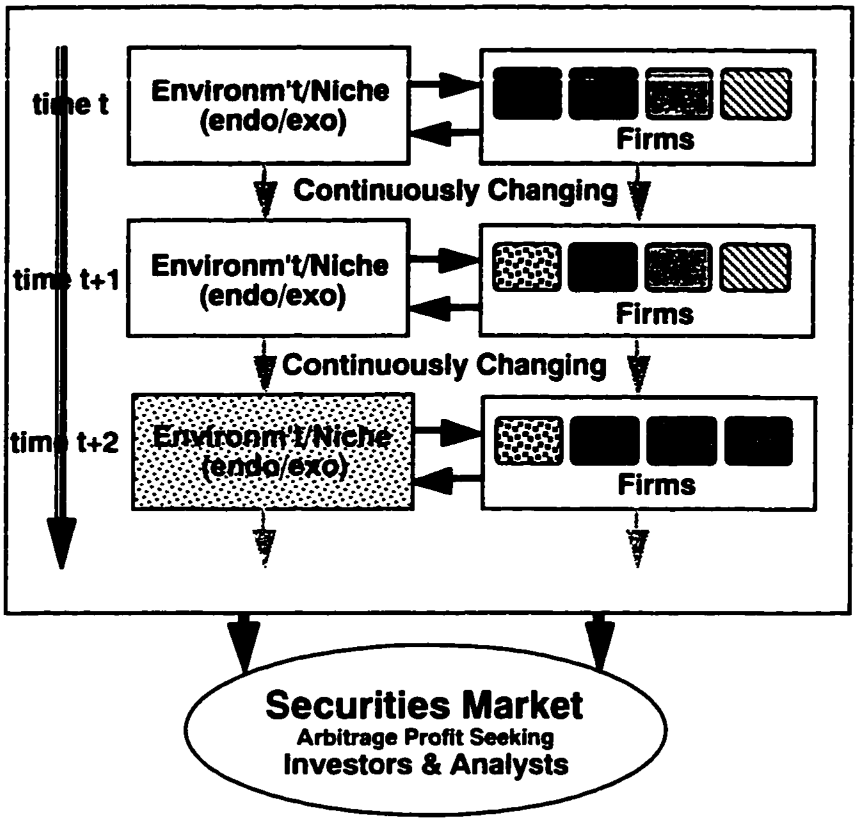


EXHIBIT 4.1: Diagram for the Dynamic Stock Return Method



REFERENCES

Alchian, Armen A. 'Uncertainty, Evolution, and Economic Theory,' *Journal of Political Economy*, 1950, **58**, pp. 211-221.

Arthur, W. B. 'Self-reinforcing Mechanisms in Economics,' in P. W. Anderson, K. J. Arrow, and D. Pines (Eds.), *The Economy as an Evolving Complex System*, Addison-Wesley, Reading, MA, 1988, pp. 9-31.

Bain, Joe S. 'Relation of Profit Rate to Industry Concentration,' *Quarterly Journal of Economics*, 1951, pp. 293-324.

Bain, Joe S. *Industrial Organization*, John Wiley, New York, NY, 2nd Ed., 1968.

Baird, I. S. and D. Sudharsan. 'Strategic Groups: A Three Mode Factor Analysis of Some Measures of Financial Risk,' working paper #931, Bureau of Economic and Business Research, University of Illinois, Urbana-Champaign, IL, 1983.

Barney, J. B. 'Strategic factor markets: Expectations, luck, and business strategy,' *Management Science*, **32**, 1986, pp. 1231-1241.

Barney, J. B. 'Asset stock accumulation and sustained competitive advantage: A comment,' *Managerial Science*, **35**, 1989, pp. 1511-1513.

Barney, J. B. 'Firm Resources and Sustained Competitive Advantage,' *Journal of Management*, **17**, 1991, pp. 99-120.

Barney, J. B. and R. E. Hoskisson. 'Strategic Groups: United Assertions and Research Proposals,'*Managerial and Decision Economics*, **11**, 1990, pp. 187-198.

Baum, J. A. C. and T. K. Lant. 'Cognitive Categorization of Competitor Groups and Perceptions of Competitive Intensity in the Manhattan Hotel Industry,' unpublished manuscript, New York University, New York, 1993.

Blashfield, R. K. 'Mixture Model Tests of Cluster Analysis: Accuracy of Four Agglomerative Hierarchical Methods,' *Psychological Bulletin*, **83**, 1976, pp. 377-388.

Bogner, W. C. and H. Thomas. 'The Role of Competitive Groups in Strategy Formulation: A Dynamic Integration of Two Competing Models,' *Journal of Management Studies*, **30**, 1993, pp. 51-67.

Bogner, W. C., J. Mahoney and H. Thomas. 'Paradigm Shift: Parallels in the Origin, Evolution, and Function of the Strategic Group Concept with the Resource-Based Ttheory of the Firm,' working paper #93-0172, University of Illinois, Urbana-Champaign, IL, 1993.

Brealey, Richard A. and S. C. Myers. *Principles of Corporate Finance*, McGraw-Hill Book Company, New York, NY, 1988.

Breeden, D. 'An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities,' *Journal of Financial Economics*, **7**, 1979, pp. 265-296.

Brittain, J. W. and J. H. Freeman. 'Organizational Proliferation and Density Dependent Selection,' in J. Kimberly and R. H., Miles (Eds.), *The Organizational Life Cycle*, Jossey-Bass, San Francisco, CA, 1980, pp.291-338.

Brown, Stephen J. and J. B. Warner. 'Measuring Security Price Performance,' *Journal of Financial Economics*, **8**, 1980, pp. 205-258.

Brozen, Yale. 'The Antitrust Task Force Deconcentration Recommendation,' *Journal of Law Economics*, **13**, 1970, pp. 279-292.

Brozen, Yale. 'Deconcentration reconsidered: Comment,' *Journal of Law Economics*, **14**, 1971, pp. 489-491.

Buckley, W. *Sociology and Modern Systems Theory*, Prentice-Hall, Englewood Clffs, NJ, 1967.

Calinski, R. B. and J. Harabasz. 'A dendrite method for cluster analysis,' *Communications in Statistics*, **3**, 1974, pp. 1-27.

Carroll, G. R. 'Concentration and Specialization: Cynamics of Niche Width in Populations of Organizations,' *American Journal of Sociology*, **90**, 1985, pp. 1262-1283.

Carroll, G. R. 'A Sociological View on Why Firms Differ,' working paper, University of California, Berkeley, CA, 1990.

Caves, Richard E. 'Industrial Organization, Corporate Strategy, and Structure,' *Journal of Economic Literature*, **28**, 1980, pp. 64-92.

Caves, Richard E. and M. E. Porter. 'From Entry Barriers to Mobility Barriers,' *Quarterly Journal of Economics*, **91**, 1977, pp. 241-261.

Chacar, A. 'Firm versus Industry Effects in Determining R&D Output,' Presented at the Academy of Management Annual Meeting, Dallas, TX, 1994.

Chen, M. 'Competing Against Competition, Not Competition,' Presented at Academy of Management Annual Meeting, Las Vegas, NV, 1992.

Cho, Seong-Ho. 'On the Stock Return Method of Determining Industry Substructure: Electronics, Petroleum, Banking, and Airlines,' Unpublished Ph.D. dissertation, The Anderson School, UCLA, Los Angeles, CA, 1996.

Cho, Seong-Ho and B. McKelvey. 'Determining industry substructure: the stock return method,' unpublished manuscript, Anderson School, UCLA, Los Angeles, CA, 1996.

Cool, K. '*Strategic Group Formulation and Strategic Group Shift: A Longitudinal Analysis of the U. S. Pharmaceutical Industry, 1963-1982*,' unpublished doctoral dissertation, Purdue University, West Lafayette, IN, 1985.

Cool, K. and D. Schendel. 'Strategic Group Formation and Performance: The Case of the U.S. Pharmaceutical Industry,' *Management Science*, **33**, 1987, pp. 1102-1124.

Cool, K. and D. Schendel. 'Performance Differences Among Strategic Group Members,' *Strategic Management Journal*, **9**, 1988, pp. 207-223.

Cool, K. and I. Dierickx. 'Rivalry, Strategic Groups, and Firm Profitability,' *Strategic Management Journal*, **14**, 1993, pp. 47-59.

Cool, K., I. Dierickx and D. Jemison. 'Business Strategy, Market Structure and Risk-Return Relationships: A Structural Approach,' *Strategic Management Journal*, **10**, 1989, pp. 507-522.

Cornell, B. and R. Roll. 'Strategies for Pairwise Competitions in Market and Organizations,' *Bell Journal of Economics*, **Spring**, 1981, pp. 201-213.

Cox, J., J. E. Ingersoll and S. A. Ross. 'A Theory of the Term Structure of Interest Rates,' *Econometrica*, **53**, pp. 385-407.

Dess, G. G. and P. S. Davis. 'Porter's Generic Strategies as Determinants of Strategic Group Membership and Organizational Performance,' *Academy of Management Journal*, **27**, 1984, pp. 467-488.

Dierickx, I. and K. Cool. 'Asset Stock Accumulation and Sustainability of Competitive Advantage,' *Management Science*, **35**, 1989, pp. 1504-1514.

Dranove, D., M. Peteraf and M. Shanley. 'The Economic Foundations of Strategic Groups Theory,' discussion paper #93-59, Kellogg School of Management, Northwestern University, Evanston, IL, 1993.

Duda, R. O. and P. E. Hart. *Pattern Classification and Scene Analysis*, Wiley, New York, NY, 1973.

Fama, E. F. 'The Behavior of Stock Market Prices,' *Journal of Business*, **January**, 1965, pp. 34-105.

Fama, E. F. *Foundations of Finance*, Basic Books, New York, NY, 1976.

Fama, E. F. and K. R. French. 'The Cross-Section of Expected Stock Returns,' *Journal of Finance*, **47**, 1992, pp. 427-465.

Fama, E. F. and M. Blume. 'Filter Rules and Stock Market Trading Profits,' *Journal of Business*, **January**, 1966, pp. 226-241.

Fiegenbaum, A. and H. Thomas. 'Industry and Strategic Group Dynamics: Competitive Strategy in the Insurance Industry, 1970-1984,' *Journal of Management Studies*, **30**, 1993, pp. 69-105.

Fisher, Frank M. and J. J. Mcgowan. 'On the Misuse of Accounting Rates of Return to Infer Monopoly Profits,' *American Economic Review*, **73**, 1983, pp. 82-96.

Fombrun, C. J. and E. J. Zajac. 'Structural and Perceptual Influences on Intraindustry Stratification,' *Academy of Management Journal*, **30**, 1987, pp. 33-50.

Frazier, G. L. and R. D. Howell. 'Business Definition and Performance,' *Journal of Marketing*, **47**, 1983, pp. 59-67.

Friedman, J. H. and L. C. Rafsky. 'Multivariate Generalizations of the Wald-Walfowitz and Smirnov Two-Sample Tests,' *Annals of Statistics*, **7**, 1979, pp. 697-717.

Gause, G. F. *The Sturggle For Existence*, Hafner (Reprinted in 1964 by Williams & Wikins, Baltimore, MD), New York, 1934.

Ghemawat, Pankaj. 'Resources and Strategy: An IO Perspective,' working paper, Harvard University, Cambridge, MA, 1991.

Grant, R. M. and A. P. Jammine. 'Performance Differences Between the Wrigley/Rumelt Strategic Categories,' *Strategic Management Journal*, **9**, 1988, pp. 336-346.

Gripsrud, G. and K. Gronhaug. 'Strategy and Structure in Grocery Retailing: A Sociometric Approach,' *Journal of Industrial Economics*, **33**, 1985, pp. 339-347.

Grossman, S. J. 'Futher Results on the Informational Efficiency of Competitive Stock Markets,' *Journal of Economic Theory*, **18**, 1978, pp. 81-101.

Grossmen, S. J. and J. E. Stiglitz. 'On the Impossibility of Informational Efficiency of Competitive Stock Markets,' *American Economic Review*, **70**, 1980, pp.393-408.

Hambrick, D. C. 'Some Tests of the Effectiveness and Functional Attributes of Miles and Snow's Strategic Types,' *Academy of Management Journal*, **26**, 1983a, pp. 5-26.

Hambrick, D. C. 'High Pprofit Strategies in Mature Ccapital Goods Endustry: A Contingency Approach,' *Academy of Management Journal*, **26**, 1983b, pp. 687-707.

Hannan, M. T. and J. Freeman. 'The Population Ecology of Organizations,' *American Journal of Sociology*, **83**, 1977, pp. 929-984.

Hannan, M. T. and J. Freeman. 'Structural Inertia and Organizational Change,' *American Sociological Review*, **49**, 1984, pp. 149-164.

Harrigan, K. 'An Application of Clustering for Strategic Group Analysis,' *Strategic Management Journal*, **6**, 1985, pp. 55-73.

Hartigan, J. A. *Clustering Algorithms*, Wiley, New York, 1975.

Hatten, Kenneth J. 'Strategic Models in the Brewing Industry,' unpublished doctoral dissertation, Purdue University, West Lafayette, IN, 1974.

Hatten, Kenneth J. and D. Shendel. 'Heterogeneity Within an Industry,' *Journal of Industrial Economics*, **26**, 1977, pp. 97-113.

Hatten, Kenneth J. and M. L. Hatten. 'Some Eempirical Insights for Strategic Marketers: The Case of Beer,' in H. Thomas and D. Gardner (Eds.), *Strategic Marketing and Management*, Wiley, New York, NY, 1985, pp. 275-292.

Hatten, Kenneth J. and M. L. Hatten. 'Strategic Groups, Asymmetrical Mobility Barriers and Contestability,' *Strategic Management Journal*, **8**, 1987, pp. 329-342.

Hawes, J. M. and W. F. Crittenden. 'A Taxonomy of Competitive Retailing Strategies,' *Strategic Management Journal*, **5**, 1984, pp. 275-289.

Henderson, B. D. 'The Orgin of Strategy,' *Harvard Business Review*, **November-December**, 1989, pp. 139-143.

Henderson, R. and I. Cockburn. 'Measuring Core Competence? Evidence From the Pharmaceutical Industry,' Working Paper, Sloan School of Management, MIT, Cambridge, MA, 1994.

Hirshleifer, J. *Price Theory and Applications*, Prentice-Hall, Englewood Cliffs, NJ, 1980.

Hotelling, H. 'The Most Predictable Criterion,' *Journal of Educational Psychology*, **26**, 1935, pp. 139-142.

Hotelling, H. 'Relations Between Two Sets of Variables,' *Biometrika*, **28**, 1936, pp. 321-377.

Huang, C. and R. H. Litzenberger. *Foundations for Financial Economics*, North-Holland, New York, NY, 1988.

Hunt, M. S. 'Competition in the Major Home Appliance Industry 1960-1970,' unpublished doctoral dissertation, Harvard University, Cambridge, MA, 1972.

Hunt, S. D. '*Modern Marketing Theory: Critical Issues in the Philosophy of Marketing Science*,' South-Western, Cincinnati, OH, 1991.

Hutchinson, G. E. 'Concluding Remarks,' *Cold Spring Harbor Symposium on Quantitative Biology*, **22**, 1957, pp. 415-427.

Itami, H. and T. W. Roehl. *Mobilizing Invisible Assets*, Harvard University Press, Cambridge, MA, 1987.

Jacobsen, Robert. 'The persistence of abnormal returns,' *Strategic Management Journal*, **9**, 1988a, pp. 415-430.

Jain, A. K. and R. C. Dubes. *Algorithms for Clustering Data*, Prentice-Hall, Englewood Cliffs, NJ, 1988.

Jensen, M. 'The Performance of Mutual Funds in the Period 1945-64,' *Journal of Finance*, **23**, 1968, pp. 389-416.

Johnson, D. R. 'Testing for Intraindustry Structure: Do Strategic Groups Exist?,' in '*Strategic Heterogeneity and Firm Performance in the U. S. Retailing Industry: A new Conceptual Approach*,' unpublished doctoral dissertation, UCLA, Los Angeles, CA, Chapter 4, 1995.

Johnson, R. A. and D. W. Wichern. *Applied Multivariate Statistical Analysis*, Prentice-Hall, New Jersey, 1988.

Jordan, J. 'Onthe Efficient Market Hypothesis,' *Econometrica*, **51**, 1983, pp. 1325-1343.

Katz, D. and R. L. Kahn. *The Social Psychology of Organizations*, Wiley, New York, 1966.

Kshirsargar, A. M. *Multivariate Analysis*, Marcel Dekker, Inc., New York, 1972.

Kuiper, F. K. and L. A. Fisher. 'Monte Carlo Comparison of Six Clustering Procedures,' *Biometrics*, **31**, 1975, pp. 777-783.

Lack, D. *Ecological Isolation in Birds*, Blackwell, Oxford, UK, 1971.

Lado, A. A., N. G. Boyd and P. Wright. 'A Competency-Based Model of Sustainable Competitive Advantage: Toward a Conceptual Integration,' *Journal of Management Studies*, **18**, 1992, pp. 77-91.

Lawless, M. and P. Anderson. 'Generational Technological Change: The Effects of Innovation and Local Rivalry on Performance,' *Academy of Management Journal*, **38**, (forthcoming in November), 1996.

Lawley, D. N. 'Tests of Significance in Canonical Analysis,' *Biometrika*, **46**, 1959, pp. 59-66.

Leonard-Barton, D. 'Core Capabilities and Core Rigidities: A Paradox in Managing New Product Development,' *Strategic Management Journal*, **13**, 1992, pp. 111-125.

LeRoy, S. F. '*Efficient Capital Markets and* Martingales,' Journal *of Economic Literature*, 1989, pp. 1583-1621.

Levins, R. *Evolution in Changing Environments*, Princeton University Press, Princeton, NJ, 1968.

Lippman, S. A. and R. P. Rumelt. 'Uncertain Imitability: An Analysis of Iinterfirm Differences in Efficiency Under Competition,' *Bell Journal of Economics*, **13**, 1982, pp. 418-438.

Lucas, R. E., Jr. 'Asset Prices in an Exchange Economy,' *Econometrica*, **46**, 1978, pp. 1429-1445.

MacArthur, R. H. 'Population Ecology of Some Warblers of Northern Coniferous Forests,' *Ecology*, **39**, 1958, pp. 599-619.

MacArthur, R. H. *Geographical Ecology: Patterns inthe Distrbution of Species*, Princeton University Press, Princeton, NJ, 1972.

Madsen, T. and B. McKelvey. 'Darwinian Dynamic Capability: Performance Effects of Balanced Intrafirm Selection Processes,' *Academy of Management Proceedings*, **August**, 1996, pp. 26-30.

Mascarenhas, B. and D. A. Aaker. 'Mobility barriers and strategic groups,' *Strategic Management Journal*, **10**, 1989, pp. 475-485.

Mayr, E. *Principles of Systematic Zoology*, McGraw-Hill, New York, 1969.

McGee, J. and H. Thomas. 'Strategic Groups: Theory, Research, and Taxonomy,' *Strategic Management Journal*, **7**, 1986, pp. 141-161.

McKelvey, Bill. 'Guidelines for Empirical Classification of Organizations,' *Administrative Science Quarterly*, **20**, 1975, pp. 509-525.

McKelvey, Bill. *Organizational Systematics*, University of California Press, Berkeley, CA, 1982.

McKelvey, Bill and A. A. Alchian. 'Populations, natural selection and applied organizational science,' *Administrative Science Quarterly*, **28**, 1983, pp. 101-128.

McKelvey, Bill and E. Mosakowski. 'When the Value Chain Changes: Adaptive Progression, Differing Levels of Prediction, and Positivist Science,' unpublished manuscript, Anderson School, UCLA, Los Angeles, CA, 1994.

Merton, R. C. 'An Intertemporal Capital Asset Pricing Model,' *Econometrica*, **41**, 1973, pp. 867-887.

Milligan, G. W. 'An Examination of the Effect of Six Types of Error Perturbation on Fifteen Clustering Algorithms,' *Psychometrika*, **45**, 1980, pp. 325-342.

Milligan, G. W. and M. C. Cooper. 'An examination of Procedures for Determining the Number of Clusters in a Data Set,' *Psychometrika*, **50**, 1985, pp. 159-179.

Mojena, R. 'Hierarchical Grouping Methods and Stopping Rules: An Evaluation,' *The Computer Journal*, **20**, 1977, pp. 359-363.

Montgomery, C. A. and H. Singh. 'Diversification Strategy and Systematic Risk,' *Strategic Management Journal*, **5**, 1984, pp. 181-191.

Morrison, D. F. *Multivariate Statistical Methods*, McGraw-Hill, New York, 1976.

Mosakowski, E. and B. McKelvey. 'Predicting Rent Generation in Competence-Based Competition,' in A. Heene and R. Sanchez (Eds.), *Competence-Based Strategic Management*, Wiley, New York, 1996.

Nelson, R. D. 'The Co-evolution of Technology, Industrial Structure, and Supporting Institutions,' *Industrial and Corporate Change*, **3**, 1994, pp. 47-64.

Nelson, R. R. 'Why Do Firms Differ, and How Does it Matter?,' *Strategic Management Journal*, **12**, 1991, pp. 61-74.

Nelson, R. R. and S. G. Winter. 'Neoclassical vs. Evolutionary Theories of Growth,' *Economic Journal*, **84**, 1974, pp. 886-905.

Nelson, R. R. and S. G. Winter. *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge, MA, 1982.

Newman, H. H. 'Strategic Groups and the Structure-Performance Relationship: A Study with Respect to the Chemical Process Industries,' unpublished doctoral dissertation, Harvard University, Cambridge, MA, 1973.

Newman, H. H. 'Strategic Groups and the Structure-Performance Relationship,' *Review of Economics and Statistics*, **60**, 1978, pp. 417-427.

Oster, S. 'Intraindustry Structure and the Ease of Strategic Change,' *Review of Economics and Statistics*, **64**, 1982, pp. 376-384.

Peteraf, M. 'Intra-Industry Structure and Response Toward Rivals,' *Journal of Managerial and Decision Economics*, **14**, 1993, pp. 519-528.

Peteraf, M. and M. Shanley. 'Getting to Know You: A Theory of Strategic Group Identity,' unpublished manuscript, Kellogg School, Northwestern University, Northwestern, IL, 1993.

Peters, R. H. *A Critique for Ecology*, Cambridge University Press, Cambridge, England, 1991.

Pianka, E. R. *Evolutionary Ecology* (5th ed.), Harper & Row, New York, 1994.

Pillai, K. C. S. *Statistical Tables for Tests of Multivariate Hypotheses*, Statistical Center, University of the Philippines, Manila, 1960.

Popper, K. R. *The Logic of Scientific Discovery*, Harper & Row, New York, German version, 1935, 1959.

Porac, J. and H. Thomas. 'Taxonomic Mental Models in Competitor Definition,' *Academy of Management Review*, **15**, 1990, pp. 224-240.

Porac, J. and H. Thomas. 'Cognitive Categorization and Subjective Rivalry Among Retailers in a Small City,' *Journal of Applied Psychology*, **79**, 1994, PP. 54-66.

Porac, J., H. Thomas and B. Emme. 'Understanding Strategists' Mental Models of Competition,' in G. N. Johnson (Ed.), *Business Strategy and Retailing*, Wiley, New

York, 1987, pp. 59-79.

Porac, J., H. Thomas and C. Baden-Fuller. 'Competitive Groups as Cognitive Communities: The Case of Scottish Knitwear Manufacturers,' *Journal of Management Studies*, **26**, 1989, pp. 397-416.

Porac, J., H. Thomas, F. Wilson, D. Paton and A. Michaelson. 'The Ccognitive Organization of Competition: The Case of Scottish Knitwear,' working paper #93-0148, Bureau of Economic and Business Research, University of Illinois, Urbana-Champaign, IL, 1993.

Poter, M. E. *Interbrand Choice, Strategy, and Bilateral Market Power*, Harvard Economic Studies, Harvard University Press, Cambridge, MA, 1976.

Porter, M. E. 'The Structure Within Industries and Companies' Performance,' *Review of Economics and Statistics*, **61**, 1979, pp. 214-227.

Porter, M. E. *Competitive Strategy*, Free Press, New York, 1980.

Porter, M. E. 'Strategic Interaction: Some Lessons from Industry Histories for Theory and Antitrust Policy,' in S. Salop (eds.), Strategy, *Predation and Antitrust Analysis*, Bureau of Economics, Federal Trade Commission, Washington D.C., 1981a.

Porter, M. E. *Competitive Advantage*, Free Press, New York, 1985.

Porter, M. E. 'From Competitive Advantage to Corporate Strategy,' *Harvard Business Review*, **65**, 1987, pp. 43-59.

Prahalad, C. K. and G. Hamel. 'The Core Competence of the Corporation,' *Harvard Business Review*, **68**, 1990, pp. 78-91.

Ramanujam, V. and P. Varadarajan. 'Research on Corporate Diversification: A Synthesis,' *Strategic Management Journal*, **10**, 1989, pp. 523-551.

Ramsler, M. 'Strategic Groups and Foreign Market Entry in Global Banking Competition,' unpublished doctoral dissertation, Harvard University, Cambridge, MA, 1982.

Rao, C. R. *Linear Statistical Inference and its Applications*, Wiley, New York, 1973.

Reed, R. and R. J. DeFillippi. 'Causal Ambiguity, Barriers to Imitation, and Sustainable Competitive Advantage,' *Academy of Management Review*, **15**, 1990, pp. 88-102.

Reevis-Comer, K. 'A Historical Comparison of Resource-Based Theory and Five Schools of Thought Within Industrial Organizational Economics: Do We Have A New Theory of the Firm?,' *Journal of Management*, **17**, 1991, pp. 121-154.

Reger, R. K. '*Competitive Positioning in the Chicago Banking Market: Mapping the Mind of the Strategist*,' unpublished doctoral dissertation, University of Illinois, Urbana-Champaign, IL, 1988.

Reger, R. K. 'Managerial Thought Structures and Competitive Positioning,' in A. S. Huff (Ed.), *Mapping Strategic Thought*, Wiley, New York, 1990, pp. 71-88.

Reger, R. K. and A. S. Huff. 'Strategic Groups: A Cognitive Perspective,' *Strategic Management Journal*, **14**, 1993, pp. 103-124.

Roll, R. 'A Critique of the Asset Pricing Theory's Tests - Part 1: On Past and Potential Testability of the Theory,' *Journal of Financial Economics*, **32**, 1977, pp. 129-176.

Roquebert, J. A., P. J. Andrisani and R. L. Phillips. 'The Relative Contribution to SBU Profitability of Industry, Corporate, and SBU Effects,' presented at the Academy of Management Annual Meeting, Dallas, TX, 1994.

Rosch, E. 'Principles of categorization,' in E. Rosch and B. Lloyd (Eds.), *Cognition and Categorization*, Erlbaum, Hillsdale, NJ, 1978, pp. 27-48.

Ross, S. A. 'The Interrelations of Finance and Economics: Theoretical Perspectives,' *Americal Economic Review*, **77**, 1978, pp. 29-34.

Rumelt, Richard P. *Strategy, Structure, and Economic Performance*, Harvard University Press, Cambridge, MA, 1974.

Rumelt, Richard P. 'Diversification Strategy and Profitability,' *Strategic Management Journal*, **3**, 1982, pp. 359-369.

Rumelt, Richard P. 'Towards a Strategic Theory of Firm,' in R. B. Lamb (Ed.), *Competitive Strategic Management*, Prentice-Hall, Englewood Cliffs, NJ, 1984, pp. 556-570.

Rumelt, Richard P. 'Theory, Strategy, and Entrepreneurship,' in D. J. Teece (Ed.), *The Competitive Challenge*, Ballinger, Cambridge, MA, 1987, pp. 137-158.

Rumelt, Richard P. 'How Much Does Industry Matter?,' *Strategic Management Journal*, **12**, 1991, pp. 167-185.

Ryans, A. B. and D. R. Wittink. 'Security Returns as a Basis for Estimating the Competitive Sructure in an Industry,' in H. Thomas and D. Gardner (Eds.), *Strategic Marketing and Management*, Wiley, New York, 1985.

Samuelson, P. A. 'Proof that Properly Discounted Present Values of Assets Vibrate Randomly,' *Bell Journal of Economics*, **4**, 1973, pp. 369-374.

Sanchez, R. 'Strategic Flexibility, Firm Organization, and Managerial Work in Dynamic Markets,' *Advances, in Strategic Management*, **9**, 1993, pp. 251-291.

Scherer, F. M. *Industrial Market Structure and Economic Performance*, Houghton Mifflin Company, Dallas, TX, 1980.

Scott, J. T. *'Firm vs Industry Variability in R&D* Industry,' Grilickes (Ed), *R&D, Patents, and Productivity*, University of Chicago Press, Chicago, IL, 1984, pp. 223-245.

Sharpe, W. F. 'Mutual fund performance,' *Journal of Business*, **39**, 1966, pp. 119-138.

Sneath, P.H.A. and R. R. Sokal. *Numerical Taxonomy*, Freeman Press, San Francisco, CA, 1973.

Swaminathan, A. and J. Delacroix. 'Differentiation Within an Organizational Population: Additional Evidence From the Wine Industry,' *Academy of Management Journal*, **34**, 1991, pp. 679-692.

Tang, M. 'Generic Strategy and the Product Life Cycle,' working paper #1601-84, Sloan School of Management, MIT, Cambridge, MA, 1984.

Tang, M. and H. Thomas. 'The Concept of Strategic Groups: Theoretical Construct or Analytical Convenience,' *Managerial and Decision Economics*, **13**, 1992, pp. 323-329.

Teece, D. J. 'Economic Aanalysis and Strategic Management,' *California Management Review*, **26**, 1984, pp. 87-110.

Teece, D. J., G. Pisano and A. Shuen. 'Firm Capabilities, Resources, and the Concept of Strategy,' working paper, University of California at Berkeley, 1990.

Teece, D. J., G. Pisano and A. Shuen. 'Dynamic Capabilities and Strategic Management,' CCC working paper #94-0, Center for Research in Management, UC Berkeley, 1994.

Thomas and D. Gardner. *Strategic Marketing and Management*, Wiley, New York.

Thomas, H. and N. Venkatraman. 'Research on Strategic Groups: Progress and Prognosis,' *Journal of Management Studies*, **25**, 1988, pp. 537-555.

Treynor, J. L. 'How to Rate Mutual Fund Performance,' *Harvard Business Review*, **January-February**, 1965, pp. 63-75.

Ulrich, Dave. 'United States and Japanese Electronics Industries: Description, Taxonomy, and Selection,' unpublished doctoral dissertation, UCLA, Los Angeles, CA, 1982.

Ulrich, Dave and B. McKelvey. 'General Organizational Classification: An Empirical Test Using the United States and Japanese Electronics Industries,' *Organization Science*, **1**, 1990, pp. 99-118.

Walter, G., B. McKelvey and N. Langton. 'The Ecological Bases of Organizational Forms,' working paper, University of British Columbia, 1990.

Ward, J. H. 'Hierarchical Grouping to Optimize an Objective Function,' *Journal of the American Statistical Association*, **58**, 1963, pp. 236-244.

Waugh, F. W. 'Regression Between Sets of Variables,' *Econometrica*, **10**, 1942, pp. 290-310.

Wernerfelt, B. 'A Resource-Based View of the Firm,' *Strategic Management Journal*, **5**, 1984, pp. 171-180

APPENDIX A

Taxonomic Variables Used for Canonical Discriminant Analysis

A. Product area by business activity niche variables

Components-Manufacture
Components-Sell
Components-Distribute
Components-Design/Test
Components-Lease
Components-Other

Power-Manufacture
Power-Sell
Power-Distribute
Power-Design/Test
Power-Lease
Power-Other

Industrial-Manufacture
Industrial-Sell
Industrial-Distribute
Industrial-Design/Test
Industrial-Lease
Industrial-Other

Instruments-Manufacture
Instruments-Sell
Instruments-Distribute
Instruments-Design/Test
Instruments-Lease
Instruments-Other

Communications-Manuf.
Communications-Sell
Communications-Distribute
Communicat.-Design/Test
Communications-Lease
Communications-Other

Consumer Bus.-Manuf.
Consumer Bus.-Sell
Consumer Bus.-Distribute
Consumer Bus.-Design/Test
Consumer Business-Lease
Consumer Business-Other

Computer-Manufacture
Computer-Sell
Computer-Distribute
Computer-Design/Test
Computer-Lease
Computer-Other

Government-Manufacture
Government-Sell
Government-Distribute
Government-Design/Test
Government-Lease
Government-Other

Transportation-Manuf.
Transportation-Sell
Transportation-Distribute
Transportation-Design/Test
Transportation-Lease
Transportation-Other

Nonelectrical-Manufacture
Nonelectrical-Sell
Nonelectrical-Distribute
Nonelectrical-Design/Test
Nonelectrical-Lease
Nonelectrical-Other

B. Firm characteristics

1. Firm Size:
Total Operating Divisions
Number Plants & facilities
Number Employees
Revenues-Sales
Current Assets
Total Assets
Current Liabilities
Shareholder's Equity
Net Income

2. Macro productivity measures:
% Income To Sales
Total Assets Per Employee
Income Per Employee
Sales Per Employee
Sales By Total Assets
Return On Assets

3. Organizational diversification:
Specialization Ratio
Electronics Specialization
Electronics Related Ratio

APPENDIX B

Between Canonical Structure:

Between-class correlations between the canonical variables and the original variables*

CAN1 VARIABLES & CORRELATIONS		CAN2 VARIABLES & CORRELATIONS	
TOTAL ASSETS PER EMPLOYEE	0.988	YEAR OF INCORPORATION	0.975
NONELECTRICAL-DISTRIBUTE	0.912	ELECTRONICS SPECIALIZATION-1979	0.894
COMPONENTS-OTHER	0.861	GOVERNMENT-MANUFACTURE	0.870
POWER-DISTRIBUTE	0.861	GOVERNMENT-DESIGN-TEST	0.870
COMPUTER-DISTRIBUTE	0.818	COMMUNICATIONS-MANUFACTURE	0.859
POWER-DESIGN-TEST	0.800	INSTRUMENTS-DESIGN-TEST	-0.869
COMMUNICATIONS-SELL	0.793	TRANSPORTATION-MANUFACTURE	-0.899
COMMUNICATIONS-SELL	0.793	# COMMON SHARES-1979	-0.916
COMPUTER-SELL	0.789	NET INCOME-PROFIT-1979	-0.924
SALES PER EMPLOYEE	0.767	REVENUES-SALES-1979	-0.938
COMPONENTS-SELL	0.744	SHAREHOLDER'S EQUITY-1979	-0.947
CONSUMER-BUSINESS SELL	-0.701	CURRENT ASSETS-1979	-0.956
SALES BY TOTAL ASSETS	-0.714	NUMBER EMPLOYEES-1979	-0.956
NUMBER PLANTS AND FACILITIES	-0.729	INCOME PER IMPLOYEE	-0.975
INDUSTRIAL-SELL	-0.758	TOTAL ASSETS-1979	-0.982
INDUSTRIAL-DISTRIBUTE	-0.762	CURRENT LIABILITIES-1979	-0.984
DIVISIONS IN NON-ELECTRONICS	-0.786	INSTRUMENTS-MANUFACTURE	-0.990
CONSUMER-BUSINESS-MANUFACTURE	-0.845	TRANSPORTATION-SELL	-0.999
CONSUMER BUSINESS-LEASE	-0.920	TRANSPORTATION-DISTRIBURE	-0.999
INDUSTRIAL-MANUFACTURE	-0.958	NONELECTRICAL-OTHER	-0.999

* Note that the variables listed here have significant absolute values of correlation.