A RESOURCE-GRADIENT THEORY OF INDUSTRY COMPETITION GROUPS AND THE STOCK RETURN METHOD

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1. INTRODUCTION

McGee and Thomas (1986) and Barney and Hoskisson (1990) conclude that there are a number of significant limitations to the theory and empirical research underlying strategic group theory, an approach primarily developed by Porter (1976, 1979, 1980) and Caves and Porter (1977) in the context of industrial organization (IO) economics. Recently the narrow performance orientation of the IO view of industry structure has been broadened to include a number of alternative theoretical bases for subgrouping by Thomas and colleagues (Porac and Thomas, 1990; Tang and Thomas, 1992; Bogner and Thomas, 1993; Bogner, Mahoney, and Thomas, 1993)—tending toward a niche-based theory sensitive to competitors and environmental opportunities. A cognitive taxonomic variant has been added by Reger (1990), Reger and Huff (1993), and Peteraf and Shanley (1993). Two problems are apparent: (1) A coherent theory of industry groupings has evaporated; and (2) Empirical methods for testing the efficacy of either the original IO view or the more recent alternatives remain unresolved. As Barney and Hoskisson (1990: 190) observe, "Given the limitations of cluster analysis as a way to test the existence of strategic groups, one is forced to wonder whether strategic groups really exist, or are an artifact of clustering analysis."

Despite this pessimism about the reality of strategic groups and the soundness of the empirical findings, the fundamental importance of better understanding questions about the structure of industry phenomena cannot be diminished. Barney and Hoskisson observe that "few concepts have caught the interest of strategic management theorists as much as the concept of strategic groups" (1990: 187). Nonetheless, they conclude that industry-level strategic group theory may be replaced by the firm-level resource-based (RB) view (Wernerfelt, 1984; Teece, 1984; Barney, 1986, 1989, 1991; Rumelt, 1987; Prahalad and Hamel, 1990; Reevis-Conner, 1991; Teece, Pisano, and Schuen, 1994). In contrast, Bogner, Mahoney, and Thomas reaffirm an industry-level "integrative economic, behavioral, and cognitive perspective" (1993: 23). At the heart of this theoretical debate is the theory of how firms actually compete, survive, and gain rents, given the common resource pool commensurate with a market segment.

We propose a revised theory of industry substructure, sensitive to both industry- *and* firm-level concerns, having its roots in evolutionary ecology (Pianka, 1994). Specifically, we focus on two elements of biological and organizational competition theory: (1) The "*principle of competitive exclusion*" (Gause, 1934; Henderson, 1989), suggesting that a population of firms may compete by becoming more homogeneous, subsequently raising barriers, and colluding (IO theory), thus creating a basis of excluding other firms; and (2) The "*principle of resource partitioning*" (Lack, 1971; Carroll, 1985), suggesting that a population of firms may compete by becoming more heterogeneous from developing resource and competence differences and advantages (RB theory), that is, by shifting positions along a niche-based resource gradient.

In light of the failure to find natural groupings (Barney and Hoskisson, 1990) and the artifactuality of the *F*-test as a significance test for clusters (Johnson, 1995), the empirical resolution of the theory issues still remains out of reach. Therefore, we introduce the *stock return method* of identifying groups, showing evidence that it can produce groups reflecting statistically significant structure within the data. Our method incorporates several improvements over the approach as initially developed by Ryans and Wittink (1985)—specifically statistical significance and objective stopping rules. It avoids many of the empirical pitfalls identified by McGee and Thomas (1986) and Barney and Hoskisson (1990).

In Section 2 we review grouping theories and develop an integrative theory of industry substructure. We review empirical problems in Section 3 and develop the stock return method. In Section 4 we describe the data and analytical methods. Results are discussed in Section 5. Conclusions follow in Section 6.

2. REVISING SUBSTRUCTURE THEORY

In this section we first review problems attributed to strategic group theory, recognize a number of proposed alternatives, and then suggest an integrative revision.

2.1 THE PROBLEMS

Barney and Hoskisson (1990) identify several logical weaknesses in strategic group theory. Various alternatives have been proposed, all of which remain largely untested. The development of the RB view, as Barney and Hoskisson also note, raises the possibility that a firm-level substructure theory might replace industry-level group

theory, a further problem for the IO-based approach.

2.1.1   THE IO VIEW

Strategic group theory dates back to Hunt (1972), but gains most of its credibility from the work of Porter (1976, 1979, 1980) and Caves and Porter (1977), where industry substructure groupings are defined as consisting of firms following similar directions along key strategic dimensions. For Caves and Porter, industry subgroup *mobility barriers* assure homogeneous intragroup performance while performance of groups within an industry remains heterogeneous (see also Cool and Dierickx, 1993). Activities that ensure superior positions in the marketplace are sustained by mobility barriers preventing movement of firms into or out of subgroups. In the IO view, "…strategic groups, supported by their mobility barriers, are partly structural and partly endogenous [which is to say, they] are determined partly by the competitive environment and partly by strategic choice" (Bogner, Mahoney, and Thomas, 1993: 8). Porter (1979) observes that the mutual interdependence and knowledge of each other's reactions sets the stage for *collusive* behavior within groups (see also Dranove, Peteraf and Shanley, 1993).

The IO view is essentially a logic chain of the following kind: (1) an identified *market segment* leads to (2) upstream or downstream *strategic emphases* which lead to (3) *mobility barriers* which lead to (4) *small group interaction* and *rivalry* which leads to (5) *collusive oligopoly* which leads to (6) *rents* (Porter, 1979; Barney and Hoskisson, 1990). But there is no evidence or logic supplied suggesting that any prior cause is both *necessary* and *sufficient* to produce any later outcome (Porter, 1979; McGee and Thomas, 1986; Barney and Hoskisson, 1990) except for the "collusion leads to rents" link (Newman, 1978). Our "necessary but not sufficient" causal view follows from the 'equifinality' characteristic of organizational phenomena recognized by general systems theory some time ago (Katz and Kahn, 1966; Buckley, 1967). Strategic group researchers have invariably tried to find, in one all encompassing empirical step, groups that evince evidence of the existence of the entire set of causal factors. They have typically tried to do this by measuring elements of cause (2) along with outcome (6). Since cause (2) is not necessary and sufficient to cause outcome (6), and no evidence is included indicating that causes (1) and (3) − (5) are indeed present, it is no wonder the research program fails to show evidence that rent generating strategic groups exist. As Barney and Hoskisson say, "…despite the efforts of numerous researchers, neither the existence of strategic groups nor their implications for the performance of firms have been demonstrated (1990: 195).

Not too surprisingly, cause (2) may be the least important item to measure as an indicator of strategic groups. If resource pools exist, and if barriers, oligopolies, and collusion exist, rents should follow, whether one has or has not shown evidence of upstream or downstream strategic emphases.   As Barney and Hoskisson note, strategic group researchers assume evidence of cause (2) is evidence of cause (3) and therefore that rents should occur. This is faulty logic by strategic group theorists.   Barney and Hoskisson demonstrate that strategy could be independent of the emergence of barriers—a firm could attempt to emphasize upstream strategies and yet benefit from a downstream caused barrier—and small group size, interaction, and collusion may not be present. So, what is a good measure of a strategic group?

Why not simply measure causes (3), (4), or (5) to show evidence of strategic groups? **First**, collusion, may not be feasible to measure—even the Federal Anti-Trust Department with all its lawyers and accountants has trouble proving collusion. On the other hand, given a small group of competing firms, experience suggests to many in and outside the Anti-Trust Department that collusion and rents are likely to follow, so it is reasonable that this link in the chain could be assumed (Scherer, 1970; Newman, 1978; Hirshleifer, 1980). **Second**, then why not test for small groups, interaction and rivalry, assume collusion, and conclude in favor of strategic groups existing?   This is the cognitive taxonomic approach.   This approach does not assure that the supposed members are in fact aiming at the same resource pool, that barriers actually exist, or that anything more real than a self-report perception of rivalry exists. Nor does it assure interaction. **Third**, then what about just measuring barriers and assume interaction, rivalry and collusion? While it may not be much of a stretch to assume collusion, given small groups, interaction, and rivalry, it is something else again to assume small groups, interaction, and rivalry, simply because one has identified barriers. There is no basis for saying that existence of barriers is evidence of grouping. Barney and Hoskisson show that there is no evidence for the (3) → (4) → (5) → (6) link. Firms can have protective barriers whether they are in a group or not. Chemical, automobile, computer chip, and steel companies all have barriers but not all firms show rents. The three airline majors (American, Delta, United) have barriers and a small group, but American and United show no rents. Using Scherer's (1980) measure of "accounting profitability available to stock holders"/"accounting book value of stockholder equity," American averages 5% and United averages −3% from 1984 − 1994, (though Delta averages 18%). In the strategic group research to date, the presence or absence of the various causes is either assumed or the causal link is not well established. Since the initial "necessary" cause (1) in the chain has not been investigated, it is far too soon to be either pessimistic or optimistic about the role of strategic groups in rent generation.

By our analysis, causes (2) − (5) are not valid, reliable bases of identifying groups, leaving niches as the only

remaining possibility. Research attempting to test the effects of collusion, size, barriers, or strategic emphases makes little sense if differentiated underlying resource pools remain unidentified in a statistically significant fashion. Therefore, in our revisiting of strategic group theory and research, we will not attempt to pin down the effects of the later causes until we have established an efficacious procedure for identifying the fundamental niche-based groups. Once a set of firms has been identified as a statistically significant group, then the task of testing whether the later effects are in fact also present and causal may be undertaken.

2.1.2 RECENT ALTERNATIVES

Though mobility barriers and homogeneous performance within subgroups have been hallmarks of the IO view for over a decade, Bogner, Mahoney, and Thomas, (1993: 11) argue 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). Thus, 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. This is also shown in the Barney and Hoskisson (1990) findings.

Peteraf and Shanley (1993) discuss several factors that might cause performance to be positively (coordination, efficiency and reputation effects) or negatively (resistance to change, perceptual blind spots, suboptimizing behavior) influenced by a group effect. They note that research on substructure has shifted away from its traditional focus on performance homogeneity toward two new directions: 1) the study of *rivalry*, (Cool and Dierickx, 1993; Peteraf, 1993; Porac and Thomas, 1994); and 2) *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). In total, Bogner, Mahoney, and Thomas (1993: 18-19) list eight theoretical bases for industry subgroups:

1. Strategic choice and endogenous mobility barriers...;
2. Different organizational structures determine different strategic behavior...;
3. Path dependencies…of firms with different resource endowments...;
4. Lumpy market conditions...;
5. Spatial competition...;
6. Differential risk preferences and firm objectives...;
7. Game-theoretic formulations...;
8. Cognitive taxonomies...;

Peteraf and Shanley (1993) add a ninth, "strategic group identity," drawing on research directed toward understanding competition within ecological niches by

Gripsrud and Gronhaug (1985), Fombrun and Zajac (1987), and Baum and Lant (1993). In some of these theories, members of the group knowingly *interact* with each other, e.g., IO, rivalry, cognitive taxonomy, game theoretic, and group identity approaches.

Bogner and Thomas (1993) point out that some bases of subgroup structure are more "objective," basing group identification on traditional IO variables, such as vertical integration, size, sales based ratios, etc., whereas others are more "subjective," such as cognitive- or behavioral-based theories. They also cite research (Fombrun and Zajac, 1987; Porac, Thomas, and Emme, 1987; Reger, 1988; Porac, Thomas, and Baden-Fuller, 1989; Porac and Thomas, 1990) suggesting that objective and subjective approaches may result in different groupings. Their resolution of the potential discrepancy is to suggest that both objective and subjective groups are determined by external forces such as technological change, regulatory change, and resource allocation decisions of other firms, all of which are niche attributes.

Both Peteraf/Shanley, in developing the theory of strategic group identity, and Thomas *et al.*, in their various papers, recognize that the *ecological link* is an important basis of industry substructure. More specifically, structure is a function of characteristics of (1) the resource pool commensurate with the niche; as well as (2) competitors for resources in the pool. The niche as underlying cause is corroborated by Lawless and Anderson (1996) where they argue for niche-based rivalry without assuming consciously coordinated behavior or shared social identity. Given these arguments to base causes of substructure in ecological niche theory, and given the identification of a niche resource pool, the "interaction" within a '*competition group*' may be (1) *real*, in that one opponent competes directly against another; or it may be (2) *virtual*, in that firms compete for supplies and sales in a zero-sum resource pool and may suffer the effects of having direct market rivalries even though "opponents" may not be directly attacked or interacted with—meaning that rivalry in a niche may be virtual, not necessarily face to face. A "competition group" emerges as a result of competition for niche-based resources. It is the initial grouping underlying both the IO logic chain arguing the emergence competitive exclusion, collusion, and rent generating strategic groups, and the RB logic chain arguing the emergence of dynamic capability, resource partitioning, and rent generating '*partitioning groups*' (which we will define in Section 2.2).

A consequence of a niche-based theory of grouping is that cognitively-based grouping approaches appear either faulty or unnecessary, given the existence of niche resource based competition groups. "Cognitive" includes cognitive taxonomy, strategic emphases, differential risk preferences and firm objectives, and strategic group identity approaches. Suppose there is a market segment to be harvested, around which a competition group forms.

Given the existence of the market segment and competition grouping measured as step (1) in the IO logic chain, if cognitive groups are at odds with the market segment, the natural course of competition group development would eventually dominate the cognitive grouping, hence the latter basis of grouping is unnecessary—just measure the competition group in the first place. If, however, there is in fact no real market segment and no basis for a competition group, or the situation is so fluid that the segment and grouping bases are unfathomable, then any formation of a cognitive grouping must surely be based on pure perception and speculation with no real basis of valid grouping, resulting in a false and misleading grouping upon which to pursue the notion that some kind of grouping might lead to rents. This assertion anticipates our distinction between Gaussian and uniform resource gradients, and rests on our argument in Section 2.2 that competitive exclusion and collusion (the required active ingredients in the thesis that cognitive groupings lead to rents) are impossible absent a Gaussian resource gradient.

2.1.3 THE RB CHALLENGE

A final step in the evolution of strategic group theory bears on its relation to RB views of strategy. This approach is a firm-level theory drawing on intrafirm resources to explain the basis of sustained competitive advantage (Wernerfelt, 1984; Teece, 1984; Barney, 1986, 1989, 1991; Rumelt, 1987; and Reevis-Conner, 1990). More recently attention has turned to 'core competence' (Prahalad and Hamel, 1990), 'strategic flexibilities' (Sanchez, 1993), and 'dynamic capabilities' (Teece, Pisano, and Schuen, 1994). Resources include all of the more permanent tangible and intangible assets tied to a firm (Caves, 1980; Wernerfelt, 1984), including both its strengths and weaknesses. A basic tenet of RB theory is that differences in firms' performances are tied directly to differences in firms' resources. Two conditions thus lead to rents:

1. **Scarcity.** Barney (1991) suggests resources generating rents must necessarily be unique, inimitable, and nonsubstitutable. Given the possibility of substitution, Mosakowski and McKelvey (1996) argue that both the form and function of resource elements must be unique and difficult to imitate. Only resources whose actual form and function remain idiosyncratic can generate rents.

2. **Value.** Identifying resource value calls for a differentiation between resources that enhance a firm's performance, detract from it, or have little effect. Barney (1991) observes that resources yield rents only as long as they remain suited to their environment. However, events in a firm's rapidly changing niche may render worthless previously valuable resources. Thus value is a function of both niche and temporal effects. In this view, the link between a firm's internal operations and its niche is the basis for determining the value of internal firm resources.

While Barney and Hoskisson (1990) see RB theory as a potential *replacement* for strategic group theory, Bogner, Mahoney, and Thomas take an *integrative* stance:

> Resource-based development is a dynamic race that is scenario dependent. Changing consumer demands and managerial choices provide both opportunities and threats for future resource

development in a path dependent process (Arthur, 1988). But future choices are determined by both the firm's and competitors' resource levels. Indeed, the concepts of isolating mechanisms (Reed and DeFillippi, 1990; Rumelt, 1984), invisible assets (Itami & Roehl, 1987), firm capabilities (Leonard-Barton, 1992; Nelson, 1991), and managerial capabilities (Lado, Boyd, and Wright, 1992) require a *comparative analysis* of competitors' resource bases and environmental opportunities (1993: 21; their italics).

Summing up, strategic group theory has lost its credibility, recent alternatives have emerged, and there is debate on whether RB theory will replace or integrate with the IO approach. We now turn to commonalities underlying IO and RB theories, leaving the rest to their fate once a valid empirical test is available.

2.2 A RESOURCE-GRADIENT THEORY OF COMPETITION GROUPS

In this section we argue that competitive processes in niches underlie both IO and RB theory. We first discuss the principles of competitive exclusion and resource partitioning. Next we theorize that rents may follow from IO or RB theory, with the distribution of resources along resource gradients in the niche determining which theory is most relevant as a cause of substructure. Finally we develop an approach for identifying competition groups that works independently of the nature of the resource gradients. While a resource, such as customer 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. A niche may consist of any number of resource gradients.

2.2.1 THE PRINCIPLES OF COMPETITIVE EXCLUSION AND RESOURCE PARTITIONING

"Biologists are better guides…to business competition than economists" (Henderson, 1989: 143). We ride on the coattails of this quote from the founder of a premier strategic consulting firm to draw on the biological **principle of competitive exclusion** (Gause, 1934; Pianka, 1994), which holds that once a resource pool is saturated or reaches a zero-sum state, that is, the carrying capacity of the niche is reached wherein the growth of one species causes the decline of another, that is, the species with the higher rate of growth will eventually totally eliminate the other species. Experiments have shown this principle to be true in biology (Pianka, 1994: 249-250). Henderson sets this principle up as the basis of strategic thinking. The existence of antitrust law is witness to the same process present in classic resource pools such as petroleum, steel, railroads, telecommunications, and more recently the growth of Microsoft, though the specific causes and processes of exclusion obviously differ between nature and industry.

It is also true in biological competition that variant members of a species facing exclusion at one point on the resource gradient may be different enough to find a basis of survival at other points on the gradient, should

competition become too stringent at the prior point. This is the ***principle of resource partitioning*** (MacArthur, 1958; Levins, 1968; Lack, 1971; Carroll, 1985). Carroll uses this principle to predict that increased concentration of generalist firms enhances the life chances of specialist firms (1985: 1273), but more broadly, increased concentration leads to competitive exclusion which stimulates excluded firms to search for other points to harvest on the resource gradient (Pianka, 1994: 272-281). In changing environments, firms with high "variational-maintenance" and populations with more high variation-maintenance members also are more likely to survive (Madsen and McKelvey, 1996). *Niche separation* follows in which a population is permanently established at a different point on the resource gradient (Pianka, 1994: 253). Market segmentation is similar, with firms entering and competing in each new segment as it appears (Swaminathan and Delacroix, 1991; Lawless and Anderson, 1996).

The principle of competitive exclusion, therefore, follows from one process, competition after saturation (what population ecologists call the competition of K types, i.e., entities that survive after the carrying capacity of the environment is reached (Levins, 1968; Hannan and Freeman, 1977), and creates, in parallel, the conditions of a second process, resource partitioning (where novel and high growth r types move into new resource pools). We suggest that these two processes underlie the two dominant phases of the strategy field, respectively, IO theory and the RB view.

2.2.1.1 Competitive Exclusion <u>and</u> Resource Partitioning

Instead of Barney and Hoskisson's (1990) conjecture, that RB theory may <u>replace</u> strategic group theory, our theory integrates them. The growth or decline of IO strategic group theory and whether it explains firm performance is independent of the growth or decline of RB theory. Parallel to the competition ➔ barriers ➔ collusion ➔ rents process, the second process of resource partitioning exists, which reflects the idiosyncrasy and resource value, core competence, and strategic flexibility or dynamic capability aspects of the RB view. Given niche-based groups, rents could also follow from idiosyncratic firm-level resources as firms hone core competencies and dynamic capabilities to compete within groups. The umbrella concept is that both processes are initiated by the nature of the resource gradient.

In the IO view, competition groups live off a Gaussian resource gradient—an oligopoly of homogeneous firms colluding under the protection of mobility barriers. Thus, thirty years ago the pain killer market was focused on aspirin—a huge demand for pain killers focused on one chemical forming a Gaussian gradient—and a few giant firms competed. In this view rents come from the preservation of the Gaussian gradient.

As new pain killer chemicals were discovered, the Gaussian gradient shifted to a uniform one, resource partitioning took place, and other firms entered. Then each new resource partition itself became '*microGaussian*' as the market at that point grew, leading more competitors to enter, so that numerous firms became distributed along the gradient but also competing with each other at the several new points—a uniform (really microGaussian) distribution. Thus, in any niche there is the potential that the initial Gaussian gradient eventually will become microGaussian (uniform) because of changes in demand and technology.

In the RB view, competition groups live off a uniform resource gradient—a group of firms competing against each other by trying to sustain competitive advantage via idiosyncrasy. In this view rents come from a constant process of resource partitioning, driven by the dynamic capabilities of firms. But, at each point there is always the potential that resource partitioning will eventually become Gaussian. Thus, in the drug industry high R&D budgets drive the resource partitioning process, with each firm using R&D and patents to create and protect the Gaussian nature of a new resource partition in an increasingly uniform resource gradient. The resource gradient branching effect and the two paths toward rents are depicted in Figure 1.

>>> Insert Figure 1 about here <<<

The logic of whether the IO view or the RB view explains rent generation is as follows:

1.   It is a given that only Gaussian resource gradients support competitive exclusion (Pianka, 1994; 75). Oppositely, the availability of a uniform distribution of munificent resources at other points on the gradient would give firms an easy alternative to the zero-sum Gaussian conditions, thereby making resource partitioning an easy option.

2.   It is also a given that only uniform resource gradients support idiosyncratic core competence and dynamic capabilities. Oppositely, the availability of a large Gaussian bunching of resources at one point would remain very attractive and make a search for alternative points on the gradient much less rewarding.

3.   As the distribution underlying competitive exclusion becomes more uniform, that is, as (1) the availability of alternative resource pools increases; (2) the Gaussian hump shrinks (relatively) as the sole harvesting point on the gradient; or (3) the pressures of competitive intensity and forces leading to competitive exclusion increase, resource partitioning speeds up the search for new harvesting points on the gradient.

4.   And alternatively, if the uniform distribution underlying resource partitioning becomes more Gaussian, the speed of resource partitioning would slow down and the advantages of competitive exclusion, barriers, and collusion increase—there is more to fight over and protect.

5.   The degree to which a resource gradient persists as Gaussian or uniform, therefore, seems fundamentally a function of two aspects: (1) the niche characteristics themselves, e. g., the nature of technology and consumer taste; and (2) the dynamic capabilities firms have: (a) A gradient that is Gaussian may in fact become uniform once dynamic capabilities and altered core competencies materialize, allowing firms to tap resources heretofore unavailable, as was the case in the pain killer industry; and (b) A gradient that is uniform at the r stage may turn Gaussian once technological standards or consumer tastes stabilize, e. g., the microcomputer software industry.

6.   The degree to which resource gradients are Gaussian or uniform and

the rate at which they change appears to be inversely related. The more Gaussian the gradient distribution and, thus, the more relevant the IO view of strategy, the more the search for rents tilts in favor of change toward a more uniform distribution and RB strategy. And the more uniform the gradient and the more relevant RB theory, the more the advantage tilts toward focusing on a Gaussian build-up as a source of rents. This is hardly surprising to ecologists since it is parallel to the dynamics of specialism and generalism (Brittain and Freeman, 1980). Thus, the more specialist a firm becomes the more vulnerable it is to generalism, and vice versa. This principle fails only if the niche is truly unchanging—because of technological or market atrophy or monopoly conditions—unlikely, given current business conditions.

The appropriateness of either strategic theory, and the viability of firms thus depends on the distribution of resources along the given resource gradient, not a theorist's or firm's predisposition as to which theory is best. Furthermore, theorists' or firms' preferences for the barriers and collusions of strategic group theory or the dynamic aspects of the RB view necessarily take a subordinate position in the face of the Gaussian/uniform or stable/changing resource gradient in a niche. Both the performance of firms and the viability of explanatory theory are therefore subject to niche conditions, in this respect.

2.2.2 THE NICHE AS THE COMMON BASIS OF COMPETITION GROUPS

The principles we establish in this section are that: (1) The nature of resource pools and the nature of firms coevolve; and (2) Competition groups may be identified via the use of covariant stock return movements which are stimulated by changes in the resource pool, rather than trying to measure structure, process, or idiosyncratic resource endowments of firms directly. This is our "*niche perturbation*" approach.

2.2.2.1 Coevolutionary Niche Theory

Ecological niches are not just habitat spaces "out there" waiting to be filled. The availability of resource pools coevolves with the capabilities of living entities for harvesting them:

1. Elton (1927) defines a niche as an animal's "place in the biotic environment, *its relations to food and enemies*" (his italics). Lawless and Anderson (1996) translate this into a "population's way of earning a living." For us a niche is a *competition group's* basis of livelihood.

2. A niche is the "sum total of the adaptations of an organismic unit" (Pianka, 1994: 269). It *coevolves* as a competition group changes resource consumption capabilities.

3. A niche traditionally has been defined by ecologists in terms of the resources consumed by the resident organism (Hutchinson, 1957; Levins, 1968; MacArthur, 1972). Thus a niche is defined by the competencies firms making up an industry subgroup have available for harvesting from the resource gradients comprising their niche.

4. The resource pool is both available and within a firm's competence for harvesting, serving as the source of **revenues** critical to the long run survival and sustainable competitive advantage the firm. Revenues are defined as value returning directly to an organization from the resource pools it harvests via the goods and services constituting its outputs. Other sources of value, such as capital markets, or banks, or of legitimacy via advertising or lobbying, etc., are not revenues and, are not bases of sustained competitive advantage, though they may be of indirect consequence, especially if they are seen as sources of firm value by those who buy and sell stocks.

5. Resource pools coevolve with the emergence of organizational forms suited for harvesting the resource.

6. Each niche may contain other competitors who have also coevolved along with the target firm and are able to compete more or less effectively along the resource gradients. These competitors may be within the target organization's competition group or in other competition groups or populations.

Ecological coevolution recognizes the fundamental interdependency between the nature of firms and the nature of the niche resources available for harvesting— each changes as the other changes (McKelvey, 1982; Nelson, 1994). The competitive strengths of firms cannot be identified without knowing what is in the niche to be harvested, and what remains to be harvested is a function of the nature of resident firms. As firms within an industry compete for survival and growth, they change the nature of the niche resource pool they attempt to harvest—look what has happened by way of customer demand as microcomputer firms changed their capabilities. And as the niche changes, firms' harvesting capabilities also change if they are to compete effectively—look what has happened to business schools as "customers" have spoken via the ranking surveys. The coevolutionary process drives firms attempting to harvest the same resource pool toward having harvesting capabilities equally effective in fostering survival, though these capabilities may be different. Thus the creosote bush, apunta cactus, and joshua tree are similar in that they have desert survival capabilities, but each plant has totally different attributes. Harvard, Stanford, and MIT have very different attributes yet each survives atop the same MBA education resource pool.

2.2.2.2 Identifying Competition Groups Independent of Firms' Attributes

We theorize that competition groups are comprised of firms having more or less equally effective survival capabilities for living off a resource gradient. There are two kinds of survival capability: (1) In IO theory it means that firms have achieved similar enough factor cost and product differentiation strategies (Porter, 1980) that they are direct competitors, each with a portion of the resource pool, and thus positioned to evolve into a *strategic group* focused on a Gaussian resource gradient while at the same time competitively excluding other entrants; (2) In RB theory it means that the firms are similar in that they have achieved the dynamic capabilities and idiosyncratic resources for successful resource partitioning, allowing them to abandon the Gaussian point on the gradient in search of alternative points, thus making the gradient more uniform, or to take advantage of a uniform gradient if it already exists—they form '*partitioning groups*'.

Even though firms might have dynamic capabilities and idiosyncratic resource endowments, these do not allow them to harvest willy-nilly at will just anywhere along a uniform gradient. Rather, they will have, or will be evaluated as having, common idiosyncratic-but-equally-effective dynamic capabilities

steering them toward certain segments of the uniform gradient. If it is microGaussian, they co-vary because of the overarching niche perturbations. If the gradient becomes Gaussian, and niche separation occurs, they co-vary because of perturbations to the new niche. These features become the basis of covariant changes in the value of the firms and in their and stock return movements.

Given gradient search capabilities having comparable adaptive effectiveness (but not necessarily similar attributes), it follows that any actual or generally perceived or expected perturbation to the resource gradient, will be information potentially relevant as to the nature of the resource gradient—perturbations such as technological, customer, economic, political, or physical environmental changes, or niche competitor changes (e.g. a competing firm fails, or is acquired, or gains increased market share). Perturbations, thus, affect the value of all firms in the niche because they could affect all the firms' survival and growth. Thus:

1.   Changes in factors impinging on a niche, or changes in the harvesting capabilities of one or more residents, affect the nature of the resource gradients and availability of resources at different points on the gradients.

2.   Changes in the resource gradients affect the harvesting potential and capabilities of most firms in the group.

3.   Changes in harvesting success affect the survival and growth potential and ultimate value of most of the firms.

4.   According to the "efficient market hypothesis" the value of firms is reflected in stock returns.

5.   Therefore, changes in stock returns can be used as proxy measures of changes in the resource pool, which gives us a means of identifying firms that are members of the competition group (as we will discuss below).

By virtue of this logic chain we have an approach for identifying competition groups that may develop, by the IO view, into groups with strategic emphases, barriers, oligopoly, and rents. Or they may achieve rents and sustainable competitive advantage by developing idiosyncratic resources having value for harvesting in the host resource pool. Which ever way a competition group develops, we theorize, depends on the nature of the resource gradients in its niche, specifically whether they appear as Gaussian or uniform distributions. And which ever causal sequence is taken toward achieving rents, the niche perturbation method of identifying competition groups draws on the same process of tracking changes in the resource pool. Consequently in either case niche perturbation serves as a proxy measure for identifying members of groups. In the following section we proceed to the development of the stock return method.

3. REVISING SUBSTRUCTURE IDENTIFICATION METHOD

Suppose we start with the following statement by Tang and Thomas (1992: 323):

Empirical studies seem to confirm the existence of strategic groups (Newman, 1978; Porter, 1979; Hatten and Schendel, 1977; Tang, 1984; Oster, 1982; Frazier and Howell, 1983; Harrigan, 1985;

Dess and Davis, 1984; Cool and Schendel, 1987; Thomas and Venkatraman, 1988) (for a complete review, see McGee and Thomas, 1986).

We identify two fundamental weaknesses in the choice of taxonomic characters and statistical significance tests in the strategic group literature (McGee and Thomas, 1986) that negate this optimistic claim.

3.1 THE PROBLEMS

3.1.1 STATISTICAL SIGNIFICANCE: TYPE I ERROR

The problem with tests of statistical significance in the existing strategic group research is that they are strongly biased toward accepting subgroups as existing when in fact they do not, a Type I Error—the null hypothesis being that subgroups do not exist. The fundamental problem, that there is no adequate statistical test of the ability of clustering algorithms *not* to produce clusters when they in fact do *not* exist in the data, has long been known (Hartigan, 1975). A variety of approaches have been tried in the strategic group research, as a perusal of the foregoing empirical studies will indicate, but none of the studies avoid an artifactual result (Barney and Hoskisson, 1990).

The reason is quite straightforward. Clustering algorithms essentially minimize within-group variance and maximize between-group variance. 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 together objects that are similar and group separately objects that are different, there is a pre-test bias serving to minimize within-variance and maximize between-variance. It should come as no surprise then that the vast majority of strategic group studies, which mostly use a variant of the F-test, all claim to show that the clusters found are statistically significant and that, therefore, that strategic groups exist (McGee and Thomas, 1986; Tang and Thomas, 1992; Fiegenbaum and Thomas, 1993).

Johnson (1995) describes a study in which 1000 cluster analyses are performed on 1000 different data sets consisting of random normal deviates. An F-test is applied to the results and in 989 times out of the 1000 the clusters are "found" significant. There can be no question that the probability is almost 1 that using an F-test will lead an investigator to conclude that he or she has significant results when in fact they are not so. The inescapable conclusion is that to date we should remain extremely cautious in accepting the Tang and Thomas (1992: 323) claim that "empirical studies seem to confirm the existence of strategic groups...." Johnson (1995), drawing on Jain and Dubes (1988), develops an approach based on Friedman and Rafsky's (1979) R statistic that offers a statistical test of whether group structure exists in a data set. Though Johnson's approach works well for

Euclidean difference coefficients, it has not yet been adapted to correlation coefficients. This leads us to a second approach, which is to gain independence between clustering and statistical test by drawing on two data sets, as we will demonstrate later in the article.

3.1.2 TAXONOMIC CHARACTERS: TYPE II ERROR

In light of the fact that a nonartifactual test of significance will subject subgroup studies to much more rigorous standards than the 989/1000 acceptance rate of the currently popular *F*-test, the Type II error becomes much more important. In view of this, we have to be concerned that the existence of subgroups might be rejected as false when in fact they exist—a likely outcome if one reads the McGee and Thomas (1986) and Barney and Hoskisson (1990) papers. The Type II error turns on the likelihood that the chosen taxonomic characters validly represent overall differences and similarities among firms.

According to Bogner, Mahoney, and Thomas (1993: 8), the IO view guided most past choices of which strategic variables to use as taxonomic characters. As reviewed by McGee and Thomas (1986), the most common approach uses variables from one or more functional areas. Hatten (1974) and Hatten and Schendel (1977) use manufacturing, marketing, and structural variables; Ramsler (1982) and Oster (1982) classify subgroups on the basis of product strategies; Baird and Sudharsan (1983) base their grouping on financial strategies such as leverage and dividend payment ratio; Hawes and Crittenden (1984) and Hatten and Hatten (1985) look at marketing strategies including price and advertising; and finally, Cool and Schendel (1987) identify strategic groups in a longitudinal analysis of the U. S. 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). More recently, Fiegenbaum and Thomas (1993) follow Cool and Schendel in using scope and resource deployment.

A number of criticisms pertain to the use of the foregoing kinds of variables as taxonomic characters:

1.   *Transience*. Some classifications are based on firm strategies which are not only imitable, but changeable in nature. For example, Southwest Airline can decide to imitate Delta's strategy, and can actually pursue this strategy. But these airlines may not fall into the same group because their market drivers are fundamentally different. Mascarenhas and Aaker (1989) argue that the use of elements of a firm's strategy as taxonomic characters may not be compatible with the search for nontransitory substructure, because strategies are activities that may be easily imitated and changed. They suggest better clustering attributes to be assets and skills which persistently resist imitation and change.

2.   *Subjectivity*. Since groups are typically clustered on the basis of an arbitrarily chosen subset of the broader list of potential characters, clusters found may result primarily from the researcher's subjective choice of characters (McGee and Thomas, 1986). Since firm strategy is often complex and multidimensional, the choice of strategic dimensions used heretofore is, by contrast, limited and arbitrary.

3.   *Representativeness*. Clustering based on a narrow set of, say, one or two functional strategies, is not necessarily indicative of overall intraindustry differences and similarities, because of externalities and complementarities of factors comprising a firm's unique structure (Dierickx and Cool, 1989). Arbitrary taxonomic characters undermine the correct and objective identification of subgroups. And the likelihood of one investigator replicating a previous study of the same population is low, if the narrow set of chosen characters is not identical.

4.   Complaints may also be raised concerning the sampling, clustering algorithms, and stopping rules used:

5.   *Time*. Failure to carefully identify periods of industry stability, and sample accordingly, may lead to groupings that are confounded by two or more time periods in which different substructures prevail, exceptions being Cool (1985), Cool and Schendel (1987), and Fiegenbaum and Thomas, 1993).

6.   *Algorithms*. Clusterings are not necessarily robust across different clustering algorithms, yet most strategic group research seems insensitive to this. Because cluster programs are algorithms, they often have different starting points and other simplifications that produce different cluster outcomes even for the same data.

7.   *Stopping rules*. Choices as to how many groups to accept either result from subjective decisions by investigators or their failure to select effective analytical, more objective, stopping rules. As published, existing studies seem largely insensitive to how cluster results might reflect biases induced by these factors.

The problem of a Type II error, or "false falsification" is fundamental. Possibly, once industry subgroup research is governed by nonartifactual statistics, the results could suggest that competition group theory is false—not because groups do not exist but because the measures themselves are false indicators. Given that Popper's (1959) classic emphasis of falsification is often taken as the keystone to proper scientific method (Hunt, 1991), failure to reject the null hypothesis of no subgroups reasonably might be interpreted by some as rejection of industry subgroup theory. In this context, it is important to remember that the various issues raised in this section all serve to produce findings likely to lead to *false* falsification.

All of the deficiencies identified in this section are correctable via a succession of studies, though most concerns are also the subject of some considerable debate over what might be the preferred approaches. Because of the differences of opinion over the most efficacious choices, there could be some advantage to our approach, which on the one hand bypasses some of the character based issues in favor of a direct classification of the underlying resource niche, and on the other attends to the choice of cluster algorithm and stopping rules. In the following section we present the stock return approach.

3.2 THE STOCK RETURN METHOD

In this section we discuss three key assumptions made in our operationalization of the stock return method and a number of advantages it appears to have over alternative approaches.

3.2.1 NICHE SPECIFIC EFFECTS AND COVARIANT STOCK RETURNS

The key principle underlying the stock return method is that any niche perturbation will cause an instantaneous

change in the stock returns of the resident competition group. There are two supporting logics implicit in this premise: (1) Perturbations affecting the niche in general or a single member of the resident competition group will affect the value of all members of the group—the "niche perturbation hypothesis," which we developed in Section 2.2.2.2; and (2) Changes in the value of firms in the competition group will show up as changes in stock return prices—the "efficient market hypothesis," to which we turn.

The efficient market hypothesis holds that new information will cause market observers, stockholders, or arbitrageurs to instantaneously reevaluate the value of the firms in the niche and alter their stock portfolios accordingly, thus affecting the return. Since (1) any niche-wide perturbation affects most niche resident firms concurrently; (2) a change in the value of one firm usually affects the relative value of most other firms in the niche; and (3) such changes in value generally disseminate quickly, the stock returns of firms in the niche will, for the most part, vary at the same time. This simultaneous common variation gives us a method to separate the covariance of niche resident groups from individual firm variances and systematic risk.

Ryans and Wittink (1985) show that a firm's stock return offers an easily available taxonomic approach, as long as one can separate (1) individual firm stock return variances; and (2) covariant industry subgroup variances; from (3) "systematic risk," (defined as broader industry and general stock market variances). Once systematic risk is eliminated, the residuals include individual firm and subgroup covariances and error terms. It is possible that the residuals might include industry effect variances; if these are significant, they should be eliminated also (See Section 4.3.1). Because individual firm variances and error terms are random, significant covariances in the residuals imply that subgroup covariances exist. Separating out the first two kinds of variances rests on the niche perturbation principle. Two courses of action first tried by Ryans and Wittink (1985) allow us to use stock returns to identify industry subgroups:

1.   Residuals from a market regression model can be used to remove systematic risk (the third kind of variance mentioned above) leaving the first two kinds—individual firm variance and subgroup covariance.

2.   Cluster and factor analysis as well as multidimensional scaling may be used to separate individual firm variances from group covariances.

In order for the method to work empirically, a critical prerequisite is that both niches and niche-specific shocks exist. If strong covariances are found in residuals, the necessary condition is satisfied as long as the stock returns reflect differential effects from the niche-specific shocks. Therefore, under the efficient market hypothesis, significant covariances in residuals assure that niches and niche-specific shocks exist. The stock return approach rests on some key assumptions, particularly the efficient market hypothesis.

We reemphasize that our stock return approach focuses only on niche-based covariance:

1.   This is not an event study—it does not matter to us that the common variance be tied to a particular perturbation or change in value of the firms within some time frame.

2.   This is not a predictive study—we are not trying to predict the value of one firm given the value or returns of other firms.

3.   This is not a performance oriented study—we make no assumptions whatsoever about performance or returns going up or down, or performance of firms within a cluster being similar.

All we require for our method to work is that the stock returns of most members in the competition group "jiggle" at the same time on most of the instances of niche perturbation and that there be a sufficient number of these to separate out extraneous systematic market events or individual firm events.

3.2.2 KEY ASSUMPTIONS

Besides the efficient market hypothesis, other assumptions discussed are that subgroup effects are independent of individual firm performance levels, and that the method might not apply to firms where stock returns only reflect aggregated information about several individual business units.

3.2.2.1 Efficient Market Hypothesis

The stock return approach assumes the efficient market hypothesis—observed security returns "fully, correctly, and instantaneously" reflect all publicly available information (Samuelson, 1973; Fama, 1976; Grossman, 1978; Grossman and Stiglitz, 1980; Jordan, 1983; LeRoy, 1989; Fama and French, 1992). Any external niche perturbations and resultant internal competitive dynamics among niche resident firms will be "efficiently" reflected in their security prices via intense market competition for arbitrage profit. Under this hypothesis, stock prices, and therefore stock returns (see Section 4.3.1 for detail) are accurate reflections of all available relevant information in the sense that self-interested rational arbitrageurs, recognizing that prices are out of line, make a profit by buying or selling stocks, thereby driving their prices back to equilibrium values consistent with available information (Ross, 1987; Huang and Litzenberger, 1988; LeRoy, 1989). An incremental change in stock price is, therefore, an immediate market equilibrium valuation of the impact of disturbances to the underlying firm (Lucas, 1978; Breeden, 1979; Cox, Ingersoll, and Ross, 1985).

Capital market efficiency has been a core tenet of finance theory since the 1960s. The stock market is "efficient" in the sense that all stock prices indicate the average positive returns from capital allocations, which are equivalent investor risks (Merton, 1973; Fama, 1976; Lucas, 1978; Cornell and Roll, 1981; LeRoy, 1989). Fama (1965) shows that the serial correlations of one day changes in the natural logarithm of price are significantly different from zero and the correlations are positive. 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 differing 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 for our approach.

Under the efficient market hypothesis the stock return is a market equilibrium valuation of firms' assets.[1] Thus a change of stock return prices[2] of firms competing in a particular niche reflects a re-equilibration[3] of the capital market's evaluation of the underlying assets of firms in the niche. Furthermore, changes in security returns due to a niche perturbation represent a market equilibrium evaluation of the impact of the environmental shock on the underlying assets. Since all the firms in the niche have coevolved toward similar assemblies of assets, structures, and behaviors in their attempt to harvest the niche's resource pool in the face of intense competition, the external shock should cause the market to reevaluate the assets of all the firms in the niche more or less simultaneously, and this re-evaluation will, therefore, appear "fully, correctly, and instantaneously" in their stock returns. This is why we can use stock returns to separate industry subgroup common variance from individual firm variances and systematic risk.

Our approach necessarily replaces insider ratings of strategic emphases or cognitive partners with outsider evaluations of firm value. Outsiders ostensibly are less prone to bias. Stock market investors presumably have more at stake in their evaluations, and are "trained" to be better evaluators of the value of firms. Other outsiders might be considered, such as suppliers, buyers, or lenders. They might be less biased than insiders, but there is no readily available measure of their valuations comparable to investors' stock market evaluations, their familiarity with all members of a competition group seems likely to be less

than that of professional stock investors which we assume dominate competition group valuations, and in the case of suppliers and buyers, they may not be well trained evaluators of firm value.

3.2.2.2 Nonperformance Component

Stock returns are inappropriate measures of group identification for two reasons:

1.   Recent studies of firm effects (Scott, 1984; Rumelt, 1991; Henderson and Cockburn, 1994; Roquebert, Andrisani, and Phillips, 1994) indicate that performance variance within industry subgroups exceeds variance between groups.

2.   Tradition in biology, which also classifies competing entities, has shown that groupings cannot depend on taxonomic characters based on performance because performance varies with the phenotype (individual organism) rather than showing no variance within a species grouping (Mayr, 1969; McKelvey, 1982)

Although it appears that the stock return approach uses a performance measure (stock returns) as a taxonomic clustering character, this is not the case. The stock return approach is concerned with group level covariance resulting from niche perturbation, not the performance of individual firms. In an efficient capital market, the stock return movement of firms in a particular niche, given a niche disturbance, will be instantaneously similar, but their performance, as measured by the relative value of the stock returns, need not be similar at all. For our purposes, stock return performance measures are not used to detect performance differences as a basis of clustering—only to show covariance.

3.2.2.3 Nonaggregate Niche Effects

In order to use stock returns in combination with niche perturbations, the stock return approach assumes that firms exist in specific nonaggregated niches, and that the stock return does not represent any kind of aggregated asset valuation. If, for example, a stock return were to represent the valuation of a diversified firm having business assets in ten niches, it is likely that the stock return method would suggest location into more than one substructure grouping. Thus, we assume that desegregated niche effects are required.

3.2.3 *ADVANTAGES*

The Ryans and Wittink (1985) stock return method[4] offers several advantages for conducting taxonomic analyses in general and our approach offers a number of more specific improvements over the Ryans and Wittink

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[1] The role of stock returns in the finance field is similar to that of product prices in neoclassical microeconomics in the sense that price is a sufficient statistic which reflects an equilibrium valuation of an asset.

[2] We follow standard finance research practice in using "returns" rather than stock market prices; returns adjust stock prices by taking into account dividend payments and stock splits.

[3] 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 re-equilibration, only that attempts in this direction, in response to niche perturbations, produce niche related common variance.

[4] In their study, Ryans and Wittink use mostly U. S. airline industry data from the CRSP data file, circa 1977-1979. They develop the basic market model that we use and they use both factor analysis and the "diameter" method of cluster analysis. Their choices as to number of factors or clusters are visual, subjective, and without reliance on more objective or statistical methods. Their cluster results generally overlap the factor results, and from the point of view of face validity, the trunk airlines mostly are in the same cluster.

study. First, the broader advantages of the Ryans and Wittink method, and then our improvements:

1.   *Number*. Lists of taxonomic characters, in well intentioned attempts to avoid narrow taxonomic representations based on unrepresentative sets of characters, are avoided in favor of a single character, without losing overall representativeness.[5]

2.   *Transience*. The problem of transient variables is avoided because the data reflect direct niche effects—once systematic risk variance is removed, the niche covariance data are totally beyond the ability of any employee to manipulate or alter because of an abrupt or fleeting change in strategy or attitude.

3.   *Feasibility*. Since securities returns are 'hard' data determined by the efficient capital market, they are replicable, readily available, and inexpensive to use.

4.   *Subjectivity*. All of the subjectivities associated with strategic, cognitive, or behavioral variables are avoided because the stock return reflects direct niche effects—subjectivities concerning choice of which theories to follow, which variables to use, which to ignore, and how many taxonomic characters are needed.

5.   *Data collection*. This method avoids problems such as questionnaire design, data collection, access to knowledgeable employees, and operationalization of such things as assets and skills to determine structural differences, as in the Mascarenhas and Aaker (1989) study, for example.

6.   *Longitudinal study*. Stock return data are well documented over time, making it easy to carry out longitudinal analyses or multiple time period studies, as in the Fiegenbaum and Thomas (1993) study.

7.   *SIC code*. Avoids having to use the SIC code as a basis of grouping—the SIC code being primitive in conception, arbitrary as to its internal logic and consistency, out of date with changing niche effects, and often based on aggregated business unit data, thus giving rise to the aggregated niche problem, and lack of much clarity in newer or more complicated industries such as electronics.

Our application of the stock return approach incorporates several conceptual and technical improvements over that used by Ryans and Wittink (1985).

1.   *Underlying theory*. Their claim that the movements of stock returns are directly related to group membership is narrowly focused on common strategies, but there has been no reliable statistically significant evidence so far that the firms with the same strategies have similar stock return movements. Our theory justifies the use of covariant stock returns.

2.   *Stopping rules*. Instead of using subjective observation for determining the optimal number of clusters in the data, as Ryans and Wittink do, we adopt analytical stopping rules proven in the clustering literature to be most effective.

3.   *Statistical significance*. In search of a nonartifactual method of ascertaining statistical significance, we conduct a canonical discriminant

analysis using additional data and variables totally independent of the stock return sample. Ryans and Wittink offer no statistical test.

4. METHOD

4.1 POPULATION AND SAMPLE

The target population consists of 684 publicly held electronics firms in the United States as identified in the 1980 *Electronic News Financial Fact Book and Directory*. From this population, we chose a subpopulation meeting two criteria: (1) Listed on the NASDAQ Exchange with complete information over our designated time period (all 52 weeks of 1979), and (2) Shows high specialization in a single business. Our sample includes all 94 members of this subpopulation.

Regarding the first criterion, only electronics firms which are listed on the NASDAQ Exchange and have complete stock returns over our designated time period, as recorded on the University of Chicago's Center for Research in Security Prices (CRSP) data tapes, are included in the sample data. NASDAQ firms are generally smaller in size than those firms listed on the AMEX or NYSE, and they tend to concentrate on a single or fewer niches. Therefore, the industry substructure of firms in the NASDAQ is likely to be detected more effectively with the stock return approach. Out of 60 defined niches in the electronics industry (Ulrich and McKelvey, 1990), the sample firms, on average, are involved in only 4.17 niches (see Exhibit 2).

Second, the activities of the sample firms should conform to Rumelt's (1974) specialization ratio of greater than 70 percent. Since they are involved in multiple businesses across industries and thus may represent aggregated niche effects, 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. (Montgomery and Singh, 1984; Grant and Jammine, 1988; and Ramanujam and Varadarajan, 1989). Firms with over a 70 percent specialization ratio are regarded as dominant single business firms (Rumelt, 1974, 1982). The average specialization ratio for our subpopulation is 89%, well above the lower bound.

4.2 VARIABLES

For each company in the sample, a complete set of 52 weekly stock returns in 1979 and 78 numerical taxonomic characters[6] are used. While the stock return approach uses

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[5] 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. The stock return 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, etc. On the face of it, stock return variance is not a firm attribute at all—it is a market movement. That is what is unique about this approach. It does not require choosing one or a few from many descriptive attributes, is readily available, and yet it appears to have taxonomic usefulness.

only stock returns for clustering, the 78 non-stock return variables are used for testing the statistical significance of the clusters found via the stock return method. The Ulrich variables consist of 60 niche characters and 18 firm characters.

Stock returns. The variables we use are between-firm correlation coefficients of weekly stock return residuals (after eliminating systematic and industry risk) for the sample firms for each week of 1979. As raw data, weekly returns are used rather than daily returns because weekly returns neutralize transient shocks.[7] The variables capture magnitudes and directions of stock return movements reflecting disturbances over the sample period of 52 weeks. Since the method classifies groups on the basis of stock price variance, if firms' stock return movement patterns are similar over 52 cases, they will be categorized in the same group. The choice of 52 weeks is determined by the one year (1979) period of the Ulrich data. In principle, too short a window might produce too few niche disturbances for us to find a niche effect; too long a window could include more than one niche configuration, possibly leading to confused or ambiguous results (Fiegenbaum and Thomas, 1993).[8] In a subsequent study of three other industries, banks, petroleum, and airlines, we find that a three year window seems optimal (Cho, 1996).

Statistical test characters. For use in the canonical discriminant analysis test of statistical significance, the non-stock return taxonomic characters nominally consist of 60 variables measuring the types of business/market niches firms occupy as well as 18 variables measuring firm size, macro productivity, and organizational diversification, and the like (see Appendix 1). Sixty niches or business/market competencies in the electronics industry are defined by Ulrich (1982) and Ulrich and McKelvey (1990), resulting from combinations of 10 product/market segments (components, power, industrial, instruments, communications, consumer-business, computer, government, transportation and nonelectronic) by 6 activity types manufacture, sell, distribute, design-

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[7] Transient shocks are short term daily movements that, even at the niche perturbation level, might reflect price movements of firms in the niche due to short lived rumors, personal opinions, large block transaction pressures, misinterpretations, and so forth.

[8] We assume that niche perturbations occur more frequently than the kinds of niche changes that would lead to altered industry substructures. Thus the stock return method should work to identify substructure groups without confusion, even under changing conditions, until the changes in niche conditions are substantial enough that niches are merged into each other, and possibly because new niches emerge. The effect of window length is the subject of a subsequent study where there is no requirement to match window length to the window fitting the Ulrich data.

test, lease, and "other"). To avoid the effect of "conjoint absences" (McKelvey, 1982: 390), niche characters having no variance are deleted, leaving 67 test characters. A conjoint absence occurs when two entities appear similar because they share the absence of a character.

4.3 ANALYTICAL METHODS

In the following subsection, we break the stock return approach into two phases for cluster identification: (1) Obtain residuals from security returns; and (2) Manipulate the residuals to produce clusters.

4.3.1 STEP I: ELIMINATING SYSTEMATIC MOVEMENTS

Step I eliminates systematic risk, that is, broad effects of the national economy and industries within it (as represented by stock price movements related to changes in the overall market index), from the total variance in stock returns. For this Step, our interest lies in the spontaneous responses measured by the firm-specific portion of security returns.

Firm-specific responses are partitioned from total returns via regression analysis. The value-weighted market index from NASDAQ is used as the measure of the market movement common to all securities traded on the Exchange. This regression model estimates an intercept term a_i and the co-movement term 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 error term $e_{i,T}$. The separation between firm-specific variation and total market portfolio variation is done using the market regression model:

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

where:

r_i = weekly stock return for stock i on week T,

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

t = $5(T-1)$, where $T = 1,2,3,...,52$

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

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

$p^*_{i,t}$ = $p_{i,t} \times s_{i,t}$

$s_{i,t}$ = 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

$e_{i,T}$ = error for security i at time T,

where this is normally distributed with mean 0 and variance q_i^2

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

The residuals from the market regression model 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. Sensitivity analysis is applied to the residuals to test whether industry effects are significant, where the industry index consists of equally-weighted four digit SIC stock return means. When niche perturbation exists, the WARs will reflect such group common variances or:

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

where:

$\alpha_{i,T}$ = firm-specific factor for firm i at time T (not observable)

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

$\varepsilon_{i,T}$ = error term for security i at time T

where this is normally distributed with mean 0 and variance $q_i'^2$

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

We choose the market model over alternatives such as Treynor's (1965), Sharpe's (1966), or Jensen's (1968) indices on the basis of Roll's (1977) critique, which is that if performance is measured relative to a market index that is *ex post* efficient, the mathematics of the efficient set indicate that no security would have abnormal performance. This critique applies to Treynor's, Sharpe's, and Jensen's indices because individual stock values are all determined relative to a supposedly *ex post* efficient index, suggesting that they are misleading. Roll does not apply his critique to the market model we use.

4.3.2 STEP II: CLUSTER ANALYSIS OF THE RESIDUALS

4.3.2.1 Resemblance Coefficient

Residuals from the market regression 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 our sample data are grouped together. Specifically, the 52 WARs of each firm from the regression analysis are 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 $r_{i,j}$ is a statistic which summarizes the closeness of abnormal return movements between firm i and firm j over the time span of 52 weeks. 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, while it captures absolute distance between residuals, can not show the direction. Following convention in the Finance literature, we consider both direction and magnitude. It is possible that two firms, say Coke and Pepsi, are in a zero-sum relationship such that their niche-based stock movements are inversely related with a zero

correlation resulting. For this to be a problem in our method, all niche perturbations would have to result in zero correlations. Since not all stock movements would ever be strictly zero-sum (some niche events would be good or bad for both Coke and Pepsi), and since all firms in a niche are seldom if ever in a zero-sum relationship, we believe this problem to be insignificant.

4.3.2.2 Clustering Algorithm

We use Ward's (1963) minimum variance method for cluster analysis because it out performs most other algorithms (including the centroid method) in every respect, except for the outlier problem (Kuiper and Fisher, 1975; Blashfield, 1976; Mojena, 1977; Milligan, 1980). In order to check for robustness against outliers, those exceeding the 1, 3, 5, 7, 9 percent limits were successively deleted. Ward's method produced the same /cluster outcome whether the outliers were deleted or not. With up to 5% deletions of outliers, the outcomes are robust and classification power increases. With 7 and 9% deletions, the outcome becomes less robust and classification power decreases, but the cluster outcome is the same.

4.3.2.3 Stopping Rules

To avoid subjective bias, we apply analytic stopping rules.[9] In an evaluation of 30 stopping rules appearing in the clustering literature, Milligan and Cooper (1985) conclude that Calinski and Harabasz's Pseudo F statistic and Duda and Hart's Pseudo T^2 statistic rank first and second in effectiveness. Milligan and Cooper (1985) also show that if chosen correctly, stopping rules can effectively determine the correct number of clusters, assuming there is cluster structure in the data, an issue to which we now turn.

4.3.2.4 Statistical Test: Canonical Discriminant Analysis

In order to check whether statistically significant substructure exists in the stock return data, we conduct a canonical discriminant analysis. We achieve independence between cluster solution and test of statistical significance—lack of which plagues the use of the F-test (Johnson, 1995)—by making the statistical test on variables clearly independent from the stock return data. We have to accomplish independence this way

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[9] The 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 size of the sample and the number of clusters in the solution, respectively. The $\mathbf{B}$ and $\mathbf{W}$ terms are the between- and pooled within-cluster sum of squares and cross products matrices. The Pseudo F tests the hypothesis that k clusters are not statistically significantly different. Duda and Hart (1973) propose the Pseudo T^2 statistic or $J_e(2)/J_e(1)$ where $J_e(2)$ is the sum of within-cluster squared errors when the data are partitioned into two clusters, and $J_e(1)$ is the squared errors when only one cluster is present.

because Friedman and Rafsky's *R* (1979) has not yet been shown to be valid when applied to product-moment correlation coefficients.[10]

Starting with clusters produced by the stock return approach (four clusters in this study), and using 67 taxonomic characters from the Ulrich data, 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). The test is based on four multivariate statistics that test for separation of cluster means across the 67 taxonomic characters of the Ulrich data. They are: Wilk's Lambda, Pillai's Trace, Hotelling-Lawley's Trace, and Roy's Greatest Root (Pillai, 1960; Rao, 1973; Morrison, 1976). Significant *F* values ($p < .05$) for each multivariate statistic imply that the stock return method produces statistically significant groups.

5. RESULTS

5.1 THE PRODUCTION OF RESIDUALS

Exhibit 1 shows movements of the average WARs of the 94 firms over the 52 weeks. They approximate a normal distribution, standardized to mean = 0 and variance = 0.01, mostly within a range of ± 2%, a substantial movement, given that these are averaged weekly stock returns. 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, an error term, and are 'free' of total market movement. The assumptions required for equation (1) are all met.

>>> **Exhibit 1 about here** <<<

5.2 THE NUMBER OF GROUPS

The Pseudo *F* (Calinski and Harabasz, 1974) has its highest peak at three clusters (*F*=6.6) and its second highest peak at four clusters (*F*=6.2), and is smaller for all other clusters levels ("high" being preferred). The Pseudo T^2 statistic (Duda and Hart, 1973) drops from a high of 6.5 (two clusters) to its lowest value of 4.4 at four clusters, and bounces back up to 4.7 (five clusters) and 5.0 (six clusters) ("low" being preferred). These stopping rules suggest that there are three or four groups in our stock return data.

In this study, we take four clusters as the optimal

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[10] Douglas R. Johnson, personal communication, June, 1994. See Johnson (1995) for further discussion of Friedman and Rafsky's *R*.

solution based on the following rationale. Although the Pseudo *F*-test indicates favorably three clusters over four clusters for our data, the Pseudo T^2 test and visual dendrogram analysis tilts our choice toward four clusters. Therefore, we conclude that analyzing four clusters would be more insightful than three clusters. Since we are primarily trying to show that there is statistically significant structure in the data, and that the stock return method captures it, it seems to us that a four group solution is a more conservative test than would be true for a three group solution. In any event, the canonical discriminant analysis produces statistically significant results for both three and four cluster solutions and clearly shows four groups, so the choice of four clusters does not undermine the stock return method, our statistical results, or most importantly, the main purpose of this paper, which is to demonstrate a nonartifactual method of searching for industry substructure.

5.3 THE NATURE OF THE CLUSTERS

In the following two subsections, we first present some descriptive material about the stock return groups and then turn to statistical significance. Note that while definition of the groups is based on the stock return groups, the descriptive material and statistical test is based on the 67 independent Ulrich variables.

5.3.1 *GROUP PERFORMANCE AND DIVERSIFICATION STATISTICS*

As a way of offering some face validity to our findings about the electronics industry substructure, Table 1 describes average firm characteristics for each group. One inference is that groups are distinguishable by their size. Firms in group 1 possess the largest total assets ($504.94m) 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 the others in every aspect, while the performance relationship among the others is more mixed. Group 4 achieves comparable productivity to group 1 on a sales-per-employee basis but lags far behind in ROA and ROE; it seems comprised mostly of small, start-up, single plant firms whose employees work harder than employees in the other groups, but whose asset utilization is not yet efficiently optimized. Group 3 seems more diversified and least productive. Though the stock return method ignores performance in clustering, performance differences appear significant in separating groups 1 and 4 from 2 and 3, though there is no reason to believe collusion is the cause. In subsequent studies (Cho, 1996) we find that the stock return method (1) perfectly separates firms in major industries, such as petroleum, banking, and airlines, into the correct "face valid" group despite several inconsistencies based on the SIC code; (2) is robust over different choices of time period windows, with three year windows being optimal; and (3) shows "face valid" changes in airlines as they went through major industry

structure changes before and after deregulation.

5.3.2 *NICHE PRESENCE*

Exhibit 2 shows in which of the 60 business/market niches, defined by Ulrich and McKelvey (1990), the firms of each group show dominant presence. The columns of the niche matrix represent activities (components, power, computers, etc.) and the rows represent product/market segments (manufacturing, distribution, R&D, etc.). In terms of activity types, each group is mostly involved in manufacturing, marketing, and R&D activities, with little presence in distribution, leasing and other activities, though group 4 shows more involvement in distribution. Although group 2 is more heavily involved in manufacturing (44%), activity 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 predominantly involved in instruments (23%), Group 2 in instruments (17%) and computers (17%), Group 3 in industrial (19%) and computers (18%) and Group 4 in components (27%) and computers (34%). Groups 1 and 3 are more or less evenly spread out across a number of lesser product/market segment involvements. Group 4 is more focused with two very strong involvements and only two lesser involvements. Groups 2 and 3 are unique in that they show minor involvement in leasing.[11]

5.4 TESTING FOR STATISTICALLY SIGNIFICANT STRUCTURE

Though the stock return method produces four industry subgroups, it by itself offers no statistical confirmation that there is statistically significant structure in the data. The descriptive information in Table 1 and Exhibit 2 provides modest insight into differences among the groups, but nothing particularly striking. We now turn to the canonical discriminant analysis for statistical confirmation of the four groups based on the 67 taxonomic characters[12]

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[11] We realize that working with all 60 niche characters (cells) leaves us vulnerable to conjoint absences and cells with only one or two entries. However, via pairwise deletion, eleven cells showing both column and row zeros were eliminated from the canonical discriminant analysis, lessening the problem somewhat.

[12] For the canonical discriminant analysis we used all the characters having variance rather than weighting some as more important than others. Further, we used both niche characters and firm characters on the grounds that while the stock return groupings are totally niche based, and niche theory could be a useful basis for explaining the existence of industry subgroups, coevolutionary niche theory suggests that the actual industry subgroupings forthcoming would be based on similarities of both niche and firm attributes.

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of the Ulrich data (listed in Appendix 1).

With four clusters, three canonical discriminant functions are derived.[13] As shown in Table 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. CAN2 has an R^2 of 0.79, while CAN 3 has an R^2 of 0.71. CAN 1 explains 46% of the total common variance.

The result of multivariate analysis confirms that all possible differences among the means of the four clusters are statistically different across the 67 independent taxonomic characters, as shown in Table 3a. Wilk's Lambda is 0.01 with an F-statistic of 1.43 ($p = 0.037$). Pillai's Trace is 2.35, with $F = 1.47$ ($p = 0.025$). The Hotelling-Lawley Trace is 11.60, with $F = 1.39$ ($p = 0.056$). Roy's Greatest Root is 5.37, with $F = 2.20$ ($p = 0.01$). In three of the four tests the results of the canonical discriminant analysis are clearly significant, with the fourth test only slightly over the $p < .05$ confidence interval.

Exhibit 3 shows a graphical plot of the firms based upon the canonical scores of firms on each of the three functions. Given that only the CAN1 function is significant (Table 3b), 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. While the results of Table 1 suggest that the dominant distinction among the groups might be size, it is interesting to discover that CAN1, the only significant function, is not in any way size related. The dominant characters on CAN1 are the niche cells: industrial-manufacturing; consumer-leasing; nonelectrical-distribution, and one firm character, total assets per employee. While these four characters have function weights of 0.9+, it is important to realize that there are 67 total characters involved in the discrimination, and that there are six others in the 0.8 – 0.9 range.

All of the size characters loaded on CAN2. We had anticipated that the size characters might "drive" the solution (and frequently taxonomists avoid size characters for this reason (McKelvey, 1982: 385)). In fact, CAN2 is not significant and many other characters loaded highly on it, suggesting that the size characters did not have any significant influence on the total solution, or even on the one function they did load on.

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[13] The top 20 characters of CAN1 and CAN2, ranked by size of loading, are listed in Appendix 2.

6. CONCLUSION AND DISCUSSION

Based on coevolutionary niche forces, we develop a theory of *competition groups* that serve as the first *necessary* step in the subsequent formation of strategic groups (according to IO strategic group theory) or resource-based groups (according to the RB view). Which kind of group ultimately prevails ("*strategic*" or "*resource partitioning*") depends on the shape of the resource gradient—Gaussian or uniform. Our theory integrates IO and RB theories into a single more comprehensive approach. We also use the *stock return approach* (Ryans and Wittink, 1985) to focus on niche-level common variance as a means well suited to discovering coevolutionary competition groups. The *efficient market hypothesis* from modern finance theory, (which holds that stock returns "fully and correctly" reflect changes in firms' asset valuation, ability to cope with competitive dynamics, and general competitive position), reflects changes stemming from technological, economic, or other market disturbances affecting the value of firms, as reflected in stock returns.

In our empirical test, we first develop a market regression model for removing general economic, industry, and market effects from the stock return data. Then, using a 100% sample of a population of 94 highly specialized electronics firms listed on NASDAQ, product-moment resemblance coefficients, Ward's algorithm for clustering, and analytical stopping rules, we discover four subgroupings. Using a canonical discriminant analysis based on 67 taxonomic characters clearly independent of the stock return data, we find evidence of statistically significant structure in the electronic population we studied. A plot of the location of the 94 firms in terms of the 1st and 2nd discriminant functions shows four obviously distinct groups. Thus, our findings show that the stock return method produces statistically significant evidence of industry substructure in at least one industry, electronics, at a level where the groupings are relatively subtle, as compared to differences between major industries such as petroleum, banking, and airlines.

There are some limitations to these findings:

1. *Specialization*. Our population only includes 94 of the 684 publicly held electronics firms in the United States (circa 1979). We limit the population so as to assure high specialization and nonaggregated niche effects. The stock return method may be of limited use with firms where the results of diverse business units are aggregated, though it is possible stock return variations might reflect observers' evaluations of events in diverse business units, even though official information from multidivisional firms is aggregated.

2. *Size*. Ranging from $28 million to $500 million in total assets, our sample consists of mostly smaller firms. The evidence of substructure and of the ability of the stock return method to find it, may not generalize to larger firms. Indeed, our evidence is more "*sub*substructure" in the sense that many observers might think that our entire population already forms one homogeneous subgroup within the larger electronics industry and further differentiations might not emerge.

3. *Small window*. One year of data collection, 1979, may be too short a time to pick up many significant niche disturbances. Because the Ulrich data are only for 1979, we limit the stock return data to that year. As Exhibit 1 shows, we do find variance, and the results suggest that it is meaningful. Still, the window seems rather small and unlikely to include many of the significant niche perturbations likely to cause the niche effect to show up in stock return movements.

4. *Unknown stability*. This study does not consider the evolutionary dynamics of industry subgroups over a longer time horizon. Unlike Fiegenbaum and Thomas (1993), we have not assured that our data are from only one stable time period in the life of the population. The one year window probably helps narrow the findings to one period, but we cannot be sure. There is always the remote possibility that a significant discontinuity in the environment of the population happened right in the middle of 1979, thereby adding confusion to our findings.

We noted at the outset Barney and Hoskisson's (1990) conclusion that there are significant limitations to the theory and research underlying the strategic group concept, despite its popularity in the literature. In developing our theory we observed a number of necessary but not sufficient causal links between the emergence of a revenue pocket or niche and the formation of strategic groups as per the IO view. Not illogically, we started at the beginning of the causal chain. We have accomplished the limited objectives of this paper, which are to (1) Develop a more integrative theory of competition groups (which might or might not ever become collusive strategic groups); (2) Introduce a relatively new method of identifying competition groups based on niche-level coevolutionary forces; and (3) Provide an empirical demonstration of the stock return approach showing that in at least one instance there is evidence of statistically significant industry substructure groupings. Our results show that the stock return method can identify statistically significant competition groups, based on a nonartifactual test of statistical significance, showing rather obvious group separation, and using objective clustering methods. The main advantages of the stock return method are: (1) Data are readily available and easy to access; (2) Data collection problems and arbitrary or subjective choices are avoided; (3) Stock returns reflect broad tendencies in firm and niche attributes; and (4) Longitudinal studies are feasible.

Our study is a beginning. We focus only on the initial coevolutionary niche conditions that give rise to the formation of competition groups. A key hypothesis implicit in our theory, that the nature of the resource gradient determines whether collusive strategic groups might emerge or whether other kinds of groups more in keeping with RB theory emerge, remains untested. The ability of the stock return approach to identify groups of clear face and statistical validity in other industries, or across different industries remains untested, though a beginning in this direction is offered by Cho (1996) where he demonstrates that the stock return approach is able to identify without exception major industry groupings of obvious validity, such as banking, petroleum, and airlines, in addition to the statistical test we provide in this paper.

Since the groups we found are larger than what observers suggest is compatible with collusive behavior,

and since we found little evidence of attenuated within-group performance variance, we clearly have *not* found evidence in support of strategic groups as per the IO view. Competition groups exist in our data but they have not developed into collusive strategic groups. We offer no evidence against or in support of IO type strategic groups. We do offer a basis of identifying competition groups that is objective and feasible. From this platform, we see little to prevent researchers from studying conditions leading groups toward collusion or toward resource partitioning and niche separation. Our theory and findings may suggest a new industry structure research program: (1) Uncovering conditions leading to Gaussian or uniform resource gradients; (2) Testing for links between the nature of resource gradients and emergent of strategic or resource-based groups (and theory); and (3) Elaborating the integrative theoretical approach initiated here.

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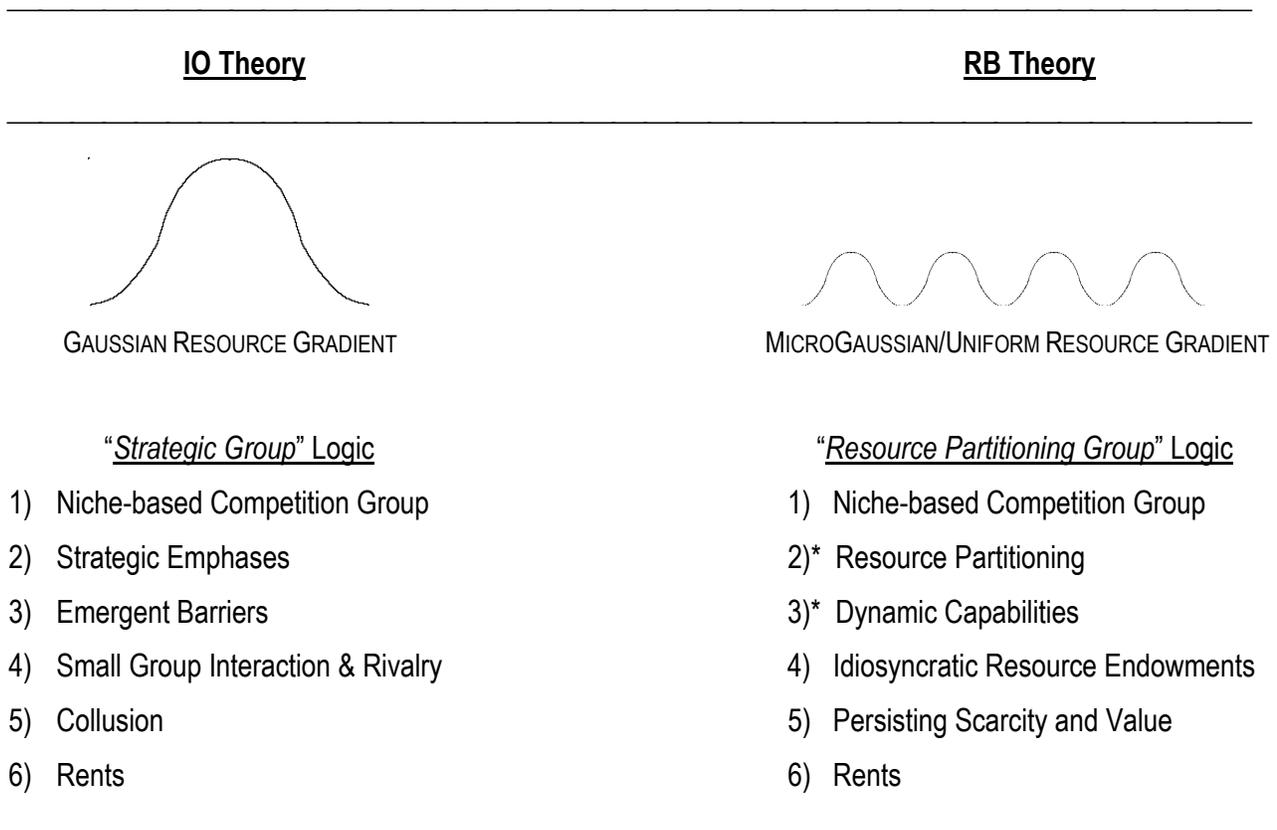
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Figure 1

Resource Gradient Branching Effect with IO and RB Logic Chains

<u>IO Theory</u>	<u>RB Theory</u>

GAUSSIAN RESOURCE GRADIENT	MICROGAUSSIAN/UNIFORM RESOURCE GRADIENT

"*Strategic Group*" Logic	"*Resource Partitioning Group*" Logic
1) Niche-based Competition Group	1) Niche-based Competition Group
2) Strategic Emphases	2)* Resource Partitioning
3) Emergent Barriers	3)* Dynamic Capabilities
4) Small Group Interaction & Rivalry	4) Idiosyncratic Resource Endowments
5) Collusion	5) Persisting Scarcity and Value
6) Rents	6) Rents

* The ordering shown assumes that the gradient already exists as uniform in the niche. But it is also possible that emergent dynamic capabilities could appear second in the "chain" and bring about resource partitioning.

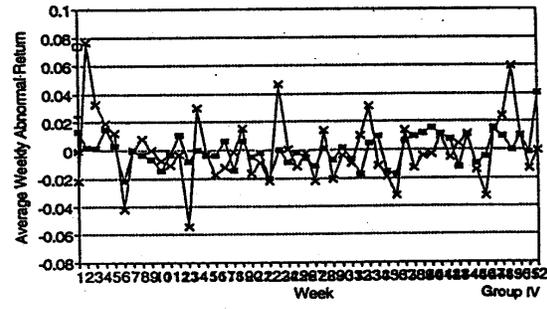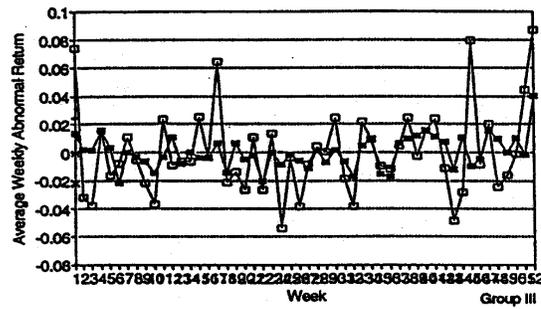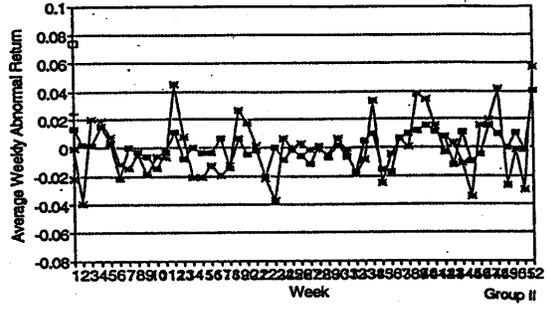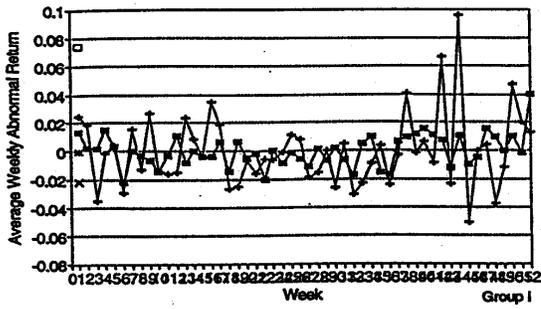Exhibit 1: Average weekly Abnormal Return (4 Groups)

Resource Gradient/Stock Return   22

Exhibit 2: 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%	1

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.

Exhibit 3: Plot of CAN1 and CAN2
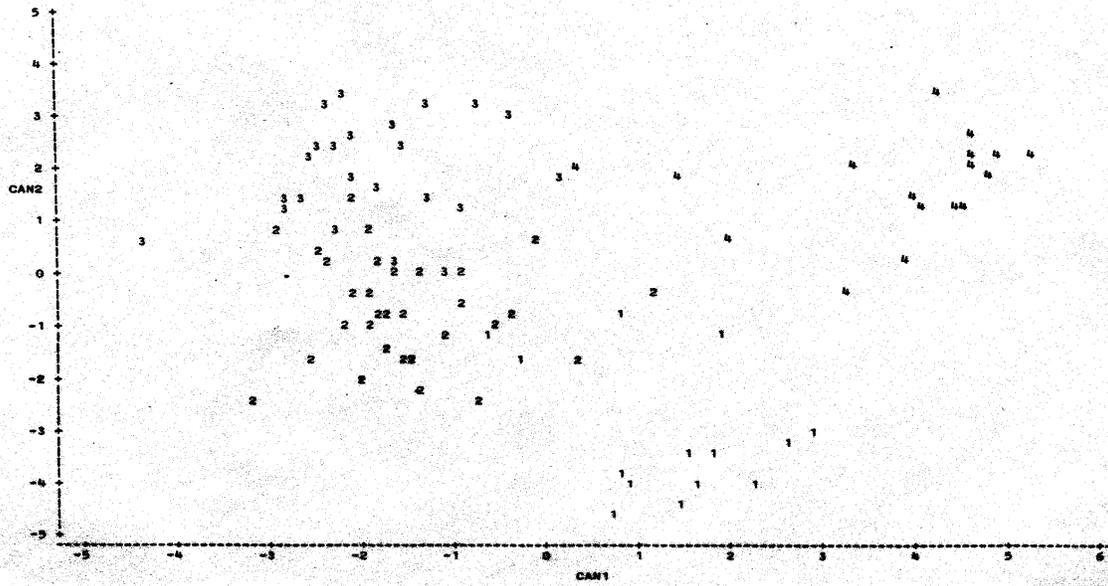
TABLE 1: Summary Statistics for Groups

	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: 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 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 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.

APPENDIX 1

Taxonomic Variables Used For Canonical Discriminant Analysis

_____

A. NICHE CHARACTERS

**(Product area by
business activity)**

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-Manufacture
Communications-Sell
Communications-Distribution
Communications-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-Manufacture
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 CHARACTERS

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