Significant Clustering: Implications for Strategic Groups Research

Charles Carroll

Faculty of Economics & Business, University of Groningen, The Netherlands

ABSTRACT

Research on strategic groups has been hindered for decades by the inability to test for significant clustering. Do firms actually clump together in distinct strategic groups? In lieu of a significance test, heavy emphasis has been placed on tests of construct validity, and the group membership-performance link has emerged as the *de facto* litmus test for the existence of strategic groups. Paradoxically, these tests for construct validity have led to distortions of the concept itself to fit the available tests. This is particularly disturbing given that the group membership-performance link is itself invalid. Several programs are now available with tests for significant clustering. A multimethod approach exploits the complementarity of permutation and Monte Carlo techniques. Strategic groups are identified by the interdependence that binds firms together, rather than the mobility barriers that keep them apart. This approach is illustrated using the European airline industry. Both theoretical arguments and industry experts predicted that strategic groups would not differ in performance. Findings support the existence of two strategic groups: low-cost airlines and full-service airlines. Results support the face validity and predictive validity of these iconic strategic groups and contradict the logically flawed group membership-performance link. This approach heals a schism in the field between those who view strategic groups as subsets of similar but *independent* firms (which is consistent with nonsignificant clustering) and those who view them as distinct groups of *interdependent*, interacting firms (a special case that emerges due to significant clustering). Nonsignificant clustering can also yield additional insights. In this example, hybrid groupings shed light on the convergence on the mainstream middle in the European airline industry.

Keywords: Strategic groups, Interdependence, Cluster analysis, Significance test, Multimethod

1. THE COEVOLUTION OF CONCEPTUALIZATION AND OPERATIONALIZATION

A strategic groups analysis can be quite helpful for researchers and practitioners alike. Strategic groups refer to sets of firms that are homogeneous within groups and heterogeneous between groups in terms of strategy. Analyzing these groups can reveal the variety of strategies that are being used within the industry and the profitability of each approach. The firms within a group are likely to react similarly to events in the environment. They are also the most direct rivals that are likely to respond to each other's strategic actions and engage each other in a mix of cooperative and competitive interactions. By identifying group members, managers can focus their attention on the most relevant rivals in the industry.

Unfortunately, in spite of all this potential, Barney and Hoskisson (1990) argue that there are serious theoretical and methodological problems undermining the validity of the entire field, and if these problems cannot be solved, then strategic groups research should be abandoned. Cattani, Porac, and Thomas (2017) disagree with that conclusion, but they regrettably acknowledge that those issues remain unresolved to this day and the findings from decades of empirical studies have been equivocal. While the field has not been completely abandoned, the level of research activity has declined (Anand, Joshi, and O'Leary-Kelly2013; Cattani, Porac, and Thomas, 2017).

In this paper, I outline how the initial methodological shortcomings led to the concept of strategic groups being distorted to fit the methods that were available at the time. To remedy that problem, I introduce two significance tests for cluster analysis in a multimethod approach. This finally allows researchers to determine if rival firms actually form distinct strategic groups. Subsequent analyses can then examine the effects of those groups. The new methods are illustrated in a brief example involving the European airline industry.

2. THE COEVOLUTION OF CONCEPTUALIZATION AND OPERATIONALIZATION

Early studies of strategic groups operationalized strategic groups using relatively simplistic dimensions selected *a priori* for the given industry (Hunt, 1972; Newman, 1973). Other studies have tried to expand the generalizability of the analysis across industries by applying broad typologies such as Porter's (1980) generic strategies (Dess and Davis, 1984; Kim and Lim, 1988) and Miles and Snow's (1978) organizational types (Parnell and Wright, 1993). Harrigan (1985) argues that typologies can be insightful in that they recognize complex interdependencies among attributes, and they are easily generalized across industries. Unfortunately, they are a bit too generic and "lack the statistical rigour of taxonomies" (p. 60) in capturing the specific nature of rivalry in a particular industry.

The use of multivariate statistics gained popularity as a means of empirically identifying groups of similar firms. The techniques that have been used include Q-type and three-mode factor analysis (Baird, Sudharshan and Thomas, 1988), multidimensional scaling (Pegels and Sekar, 1989), logit analysis (Hayes, Spence and Marks, 1983), a self-organizing neural network approach (Serrano-Cinca, 1998) among others. However, the most widely adopted technique has been cluster analysis.

2.1. The Use of Cluster Analysis

Clustering refers to densely populated regions that are separated by sparsely populated regions. This corresponds with the view of strategic groups as clusters of firms that are homogeneous within groups and heterogeneous between groups in terms of strategy. Conceptually, this seems like a good fit, but in practice it falls short.

The most widely used technique has been hierarchical cluster analysis using Ward's method and squared Euclidean distance. Step by step, Ward's method merges the pair of firms/clusters that minimizes the total within-group variance. This maximizes the homogeneity within groups and identifies the densely populated regions. However, it says nothing about the heterogeneity across groups. Are there sparsely populated regions separating these groups? Consider a sample of firms that are uniformly distributed across the strategy space with no clustering. The algorithm will still partition (slice) the firms into internally homogeneous but immediately adjacent groupings. Consequently, it is never clear if the algorithm has discovered naturally occurring groups or merely invented some groupings.

This problem has drawn harsh criticisms from prominent researchers surveyed by Meyer (1991, p. 826). "Cluster analysis, however, was characterized by several informants as a methodological stigma rather than a contribution, for '*the empiricism inherent in this method has been forever branded upon our collective backside.*'" The key concern has been that cluster analysis lacks a significance test to indicate whether or not distinct groups actually exist (Hatten and Hatten, 1987; Barney and Hoskisson, 1990; Ketchen and Shook, 1996).

This has created a schism within this field regarding the nature of strategic groups. Hatten and Hatten (1987) pay strict attention to the limitations of the methods and argue that, in the absence of a significance test, there is no justification for inferring that the analysis has discovered isolated groups. Since the algorithm will always invent homogeneous groupings, these should only be used as an analytic convenience when aggregating information associated with those strategic positions. There is no reason to assume that such arbitrary partitions would correspond to the boundaries of rivalry. The firms within a grouping might display similar reactions to events in their environment, but it is assumed that they do not constitute a cohesive group of interacting firms. Given the assumption that firms within a group are independent of each other, I refer to this as the *independent view* of strategic groups.

In contrast, Tang and Thomas (1992) argue that the concept of strategic groups is much richer than the limitations of the clustering algorithm. Strategic groups are assumed to be distinct clusters of interdependent firms that reflect the social structure of rivalry within an industry. Firms have a shared sense of identity, and they interact within each group using a mixture of cooperative and competitive interactions. Since interactions are primarily contained within each isolated group, the nature of the interactions could generate true group-effects in performance. These true group-effects would be in addition to any firm-level effects associated with holding that strategic position (associated with the independent view). Given the critical importance of interdependence among group members, I refer to this as the *interdependent view* of strategic groups.

Hatten and Hatten (1987) lament that the majority of the literature embraces the interdependent view even though a cluster analysis can only support the independent view. This has driven advocates of the interdependent view to rely heavily on tests of construct validity to justify their positions. Typically, this has revolved around the argument that firms within an industry are expected to have roughly equal levels of profitability because they are subject to the same industry structure. However, a strategic groups analysis constitutes a finer-grained analysis of that structure, thereby creating the possibility of performance differences within the industry. Mobility barriers could protect highly profitable strategic groups from entry by rivals currently located in less profitable groups. Thus, researchers only need to demonstrate differences in performance across groups to support the claim that distinct strategic groups exist in that industry. This has captured the attention of many researchers, and (for better or worse) the *group membership-performance link* has become the *de facto* litmus test for the existence of strategic groups.

Given the critical role that mobility barriers play in sustaining performance differences, Harrigan (1985) shifted the attention from the homogeneity within groups to the heterogeneity between them. "Clustering analysis generates descriptions of the boundaries segregating groups" (p. 59). She argued that the space between clusters could be used "for estimating the heights of mobility barriers which segregate strategic groups" (p. 59). McGee and Thomas (1986, p. 150) echo this advice: "Theoretical taxonomies incorporating such concepts as mobility barriers…and isolating mechanisms…can be developed to identify appropriate strategic dimensions for forming strategic groups." These dimensions reflect strategic decisions "which cannot readily be imitated by firms outside the group without substantial costs, significant elapsed time, or uncertainty about the outcome of those decisions" (p. 150). Presumably, any firm moving through the space that separates strategic groups must absorb those costs, delays, and/or uncertainties along the way, and presumably those would be proportional to the distance travelled.

This approach was very resourceful in that it attempted to squeeze more implications out of a single analysis. Unfortunately, it does so by *conflating* the closely related but theoretically distinct concepts of strategic groups and mobility barriers. Paradoxically, these concepts were conflated in an attempt to establishing their construct validity. It is also troubling that this approach relies on a static snapshot of the distance between groups to estimate the impact of the dynamic process of moving between those groups. This raises an array of issues, such as the asymmetric nature of barriers associated with moving in different directions, and the potential retaliation of incumbent firms that could vary across groups and occur independently of the distance travelled.

Still, in the absence of compelling alternatives, the focus turned to refining the process of selecting strategy variables for the cluster analysis. McGee and Thomas (1986) argue that knowledge of the specific industry must be used to identify dimensions that systematically affect profitability. Similarly, Harrigan (1985, p. 63) selected strategy variables based on regressions predicting ROI. These tips do not require a theoretical explanation; applying cluster analysis to variables correlated with performance is likely to yield clusters related to performance. Regrettably, these efforts still failed to consistently produce the desired performance differences across strategic groups, and critics seized on these results.

> The frequent use of cluster analysis is an embarrassment to strategic management…. Fuelling this contempt are the equivocal results that cluster analysis often provides. The best illustration is strategic groups research, which has been unable to consistently find a group membership-performance link. (Ketchen and Shook, 1996, p.442)

To summarize these twists and turns in the use of cluster analysis, (a) the initial idea was to identify homogeneous groups of firms with respect to strategy variables, (b) but those variables should really reflect mobility barriers, and (c) it ultimately came down to hand selecting variables that were likely to yield performance differences across groups. The operationalization seems to have wandered away from the conceptualization of strategic groups by taking a series of shortcuts to get to performance. While the motivation is understandable and the ingenuity is commendable, the decades of equivocal findings have been disappointing.

Typically, the fact that strategic groups do not consistently show differences in performance has been interpreted as a lack of support for the strategic groups concept. However, I would argue that the problem lies with the argument that performance differences should exist. Given the dramatic impact that it has had on the field, the logic of the group membership-performance link merits closer inspection.

2.2. The Group Membership-Performance Link

First, if performance differences were observed across groups, then it would be valid to infer that distinct groups must exist *and* the more profitable groups must be protected by mobility barriers. Otherwise, the performance differences would presumably level out. Notably, both conditions (strategic groups *combined with* mobility barriers) are required for sustainable performance differences to exist. However, what if performance differences were not found? In the most extreme (and logically incorrect) interpretation, if performance differences do not exist, then strategic groups themselves do not exist. A more appropriate inference given the lack of performance differences would be that *either* distinct groups *or* mobility barriers are missing.

It is possible for strategic groups to exist without mobility barriers to protect them—for example, contestable markets. Hatten and Hatten (1987) even argue that contestable markets are essential in explaining the evolution of industry structure. Further, in a world that is increasingly characterized by turbulence and hypercompetition (D'Aveni, 1994), the scrappy fighters who can survive and thrive in unprotected environments could provide more meaningful insights into contemporary strategy than the firms that are enjoying a comfortable, protected environment. This is consistent with Porter's (1990, p. 82-83) advice on preparing firms for global competition. "Domestic rivalry, like any rivalry, creates pressure on companies to innovate and improve. …. The more localized the rivalry, the more intense. And the more intense, the better." Too much protection(ism) is unhealthy. Thus, the absence of performance differences might mean that groups exist without any protective barriers, which in itself is an interesting issue for research.

Second, even if strategic groups and mobility barriers are combined, they only offer the possibility that performance differences could exist (Cool and Schendel, 1988). According to *equifinality*, firms pursuing radically different strategies could still end up achieving equal levels of profitability (Katz and Kahn, 1978; Marlin, Ketchen, and Lamont, 2007).

Third, the ability to implement a strategy might have a greater impact on performance than the choice of the strategy itself (Cool and Schendel, 1988). Consequently, within-group differences might wash out any between-group differences in performance (McNamara, Deephouse and Luce, 2003).

The theory suggests that performance differences might be found some of the time, and that is consistent with the "equivocal" findings. It is the mistaken argument that performance differences *must* exist that is not supported by the data.

> Clearly, a more qualified theoretical view [must be] developed on the performance consequences of strategic group membership. Yet empirical research maintained its focus on…direct linkages between strategic group membership and firm performance... [M]ixed results should not be surprising given the many (potentially) intervening variables. (Cool and Schenel, 1988, p. 208)

Relying on performance differences across groups *confounds* the effects of strategic groups with that of countless other variables that could influence performance. A significance test for cluster analysis would provide a more valid and direct means of establishing the existence of distinct strategic groups. Fortunately, it turns out that significance tests are already available. The next section introduces two complementary techniques in a multimethod approach.

3. SIGNIFICANCE TESTS FOR CLUSTER ANALYSIS

Since the problem of mathematically deriving a significance test for cluster analysis appears to be intractable, there has been (limited) interest in developing computationally intensive methods using permutation or Monte Carlo techniques dating back at least to the late 1960s. However, at the time that the debates about strategic groups were raging, it was generally accepted that those early efforts "do not offer much that is either well accepted, well worked out, or specific. The problem of statistical substantiation is largely unsolved at this time" (McKelvey, 1982, p. 427).

That all changed when Clarke, Somerfield and Gorley (2008) described a permutation test based on SIMPROF (a curve derived from the similarity matrix for observations). This inspired the development of the DISPROF function (using distance rather than similarity measures) in Matlab (Jones, 2015) as well as some programs written in *r* and made available in PRIMER (Clarke & Gorley, 2015) and Clustsig (Whitaker & Christman, 2014). These techniques were developed by, and targeted for, researchers in biology. Unfortunately, Matlab and the *r* programming language are not as widely used in business research. To facilitate the diffusion of these techniques for strategic groups research, I have developed a similar test in SPSS. Notably, my permutation test does not use (dis)similarity profiles. Instead, the significance test is performed directly on the statistic used in forming the clusters such as the total within-group variance in Ward's method. Further, given the inherent problems associated with permutation tests for cluster analysis, I also developed a Monte Carlo test with complementary strengths and weaknesses to exploit the advantages of a multimethod approach (Brewer and Hunter, 2006). This multimethod approach assesses the likelihood of obtaining the observed values of the clustering statistic by comparing them to two different sets of null distributions generated by complementary techniques.

3.1. The Permutation Test

In general, a permutation test empirically generates the null distribution of the test statistic by permuting (randomly shuffling) the data so the phenomenon of interest (clustering) is reduced to levels associated with random chance, while preserving (thereby controlling for) all of the other characteristics of the data. The closest approximation for cluster analysis is obtained by permuting every variable independently. This removes the effects of multivariate clustering when generating the null distribution for the statistic, but it also removes the effects of any other multivariate structure such as correlations between variables. Consequently, if the observed value looks unlikely vis-à-vis the null distribution, it is not clear if that difference is due to multivariate clustering or some other form of multivariate structure (Clarke et al, 2008; Author, 2016).

Univariate clustering has the opposite problem. Independently permuting each variable perfectly preserves the characteristics of each variable, so it fails to remove the effects of univariate clustering from the null distribution. Consequently, the observed value of the clustering statistic does not look unusual compared to that null distribution, so the test cannot detect univariate clustering (Clarke et al, 2008; Author, 2016).

On the bright side, Author (2016) found that the permutation test is remarkably powerful and accurate under the right conditions. When several variables are involved in the clustering, the test's ability to accurately distinguish clusters was so good that the test pattern had to be revised twice (making it more difficult) before it posed any kind of challenge for this technique. Ironically, the variables in this condition were also highly correlated, but those correlations resulted directly from the positioning of the clusters. Clarke et al (2008) explained this effect in terms of a duality involving *clustered observations* and *correlated variables*: correlated variables do not cause clustering, but clustering tends to cause correlated variables. The former (correlations without clustering) leads to high Type I errors, but the latter (correlations caused by clustering) results in remarkable precision in terms of extremely low Type I and Type II error rates. So this method is promising, but it requires additional validity checks to avoid being misled by statistical artefacts.

3.2. The Monte Carlo Test

The Monte Carlo test also generates a null distribution for the clustering statistic, but it does so by creating simulated data that mimic the original data as closely as possible while imposing the conditions of the null hypothesis (no clustering of observations). Unimodal distributions are tweaked to empirically identify the best fit for each input variable. If univariate clustering exists, then that multimodal distribution is matched as closely as possible with a unimodal distribution that smooths out any peaks and valleys. This removes the univariate clustering. Similarly, the autofit function removes any multivariate clustering by replicating the correlation matrix while ignoring any multivariate clustering. So the procedure generates a simulated population that is free of clusters but otherwise resembles the original data as closely as possible. The null distribution for the clustering statistic is generated by repeatedly drawing a fresh sample from the simulated population and running the cluster analysis on it.

3.3. A Multimethod Approach

A multimethod approach tries to combine techniques that do not share the same weaknesses.

> Our individual methods might be flawed, but fortunately the flaws in each are not identical. A diversity of imperfection allows us to combine methods, not only to gain their individual strengths but also to compensate for their particular faults and limitations. (Brewer and Hunter, 2006, p. 4)

For instance, the permutation test cannot detect univariate clustering, because those effects are unavoidably included in the null distribution. In contrast, the Monte Carlo test removes those effects when generating the null distribution. Hence, it can catch the univariate clustering that the permutation test would miss.

The permutation test also cannot distinguish between clustered observations and correlated variables—the troublesome duality noted by Clarke et al (2008). Hence, if the permutation test is significant, there is the nagging possibility that the observed value on the clustering statistic was due to correlated variables rather than clustered observations. Half a century of struggling with this problem underscores the notorious difficulty of isolate the effects of clustering, but it is relatively easy to isolate the effects of correlations. Removing that effect would take a big step forward in disentangling this duality.

The Monte Carlo test assesses the correlation matrix for the given dataset and replicates it in the simulated population. Samples from the simulated population are used to generate the null distribution for the clustering statistic given that the variables are correlated and there is no clustering in the data. If the Monte Carlo test is statistically significant, that means that there is very little chance of obtaining that value on the clustering statistic from data that just has correlations without clustering. Hence, the Monte Carlo test serves as a validity check for the permutation test by specifically ruling out the greatest threat.

While a Monte Carlo test can control for the correlation matrix, its Achilles' heel is that it might overlook other idiosyncrasies of the original data when generating the simulated data. In contrast, the greatest strength of a permutation test is that it works with the original data itself. This avoids the need to make potentially biased assumptions, and the effects of any idiosyncrasies in the data are automatically controlled for in the null distribution. Again, if the results agree, "their convergent findings can be accepted with far greater confidence than any single method's findings would warrant" (Brewer and Hunter, 2006, p. 4).

The two significance tests address the historical methodological problem in strategic groups research by determining if rival firms form discrete clusters (distinct strategic groups). This eliminates the need to rely on demonstrably invalid tests of construct validity such as the group membership-performance link. This approach is illustrated in the following example involving the European airline industry.

4. METHODS

4.1. Sample

This example uses data on European airlines (n=26) from 2012 published by Daft and Albers (2015). Readers are encouraged to see their article for more details regarding the industry and strategy data. Additional data on performance (n = 22) were obtained from annual reports. See Table 2 (note *a*) for the four firms that are missing performance data.

4.2. Analysis

A hierarchical cluster analysis was performed on 17 strategy variables (see Appendix) using Ward's method and squared Euclidean distance. For brevity and readability, only the solutions containing 1 to 12 clusters are shown. Both the permutation test and the Monte Carlo test used 999 iterations to generate the null distributions of the clustering statistic (total within-group variance). The Monte Carlo method draws a fresh sample for each iteration from the cluster-free simulated population (N=10,000 firms). Scatter plots were generated using discriminant analysis to show the greatest separation of the strategic groups. Finally, differences in performance (market share, profit margin, and return on assets (ROA)) were tested using a MANOVA and a series of one-way ANOVAs.

5. RESULTS

5.1. Cluster Analysis

Table 1 shows the clustering statistic for Ward's method (total within-group variance) and the associated p-values at each step in the agglomeration schedule. In Figure 1, the solid lines in the associated scree plots represent the observed value using the original data; hence the lines are identical in both plots. The dotted lines indicating the cut-offs for extreme values in the null distributions generated by each technique. Note that only the lower dotted line is relevant in this one-tailed significance test. Typically, there are only a few, if any, points at which the solid line drops below the lower cut-off line indicating a significant result ($p<0.05$). Surprisingly, the permutation test flagged every cluster solution up to 12 groups as statistically significant ($p=0.001$). This pattern tends to be associated with highly correlated variables, so it is not clear if there is actually any clustering in the data. The Monte Carlo test controls for correlations, and it only flagged the two-cluster solution as significant ($p=0.050$). That scree plot looks more like the typical results. While the permutation test appears to be affected by the correlations among the variables, the significant Monte Carlo test for the two-cluster solution rules out the possibility that those distortions are due solely to correlations in the absence of clustering. Since the complementary significance tests agree that the two-cluster solution is significant, these two distinct strategic groups will be the primary focus of subsequent analyses and interpretation within the *interdependent view*.

By comparing these two groups on the strategy variables, it appears that they reflect the traditional *legacy (full-service) airlines* and *low-cost (no-frills) airlines*. Firms in the group labelled full-service airlines tend to offer a variety of classes (such as economy, business, first class), more in-flight entertainment, and a variety of other services such as checked baggage and catering that are included in the ticket price. They also access the more convenient and more expensive primary airports using a hub-and-spoke design, which means they need a variety of aircraft: small planes for the spoke routes, and larger, long-haul planes to fly hub-to-hub. They also tend to form alliances with other airlines to feed their hubs.

In contrast, firms in the group labelled low-cost airlines tend to access less expensive secondary airports using point-to-point routes and flying smaller planes to efficiently handle the lighter traffic and shorter routes. This also allows them to operate more

Table 1: The observed value of ward's clustering criteria (total within-group variance) and the pvalues from the permutation test the monte Carlo test for 1 to 12 clusters

Number of groups	Ward's criteria	Permutation test	Monte carlotest
1	352.483	1.000	0.070
2	250.759	0.001	0.050
3	216.165	0.001	0.095
4	182.883	0.001	0.082
5	161.196	0.001	0.117
6	141.483	0.001	0.122
7	122.682	0.001	0.086
8	111.583	0.001	0.136
9	101.013	0.001	0.203
10	90.768	0.001	0.241
11	81.804	0.001	0.284
12	72.962	0.001	0.301

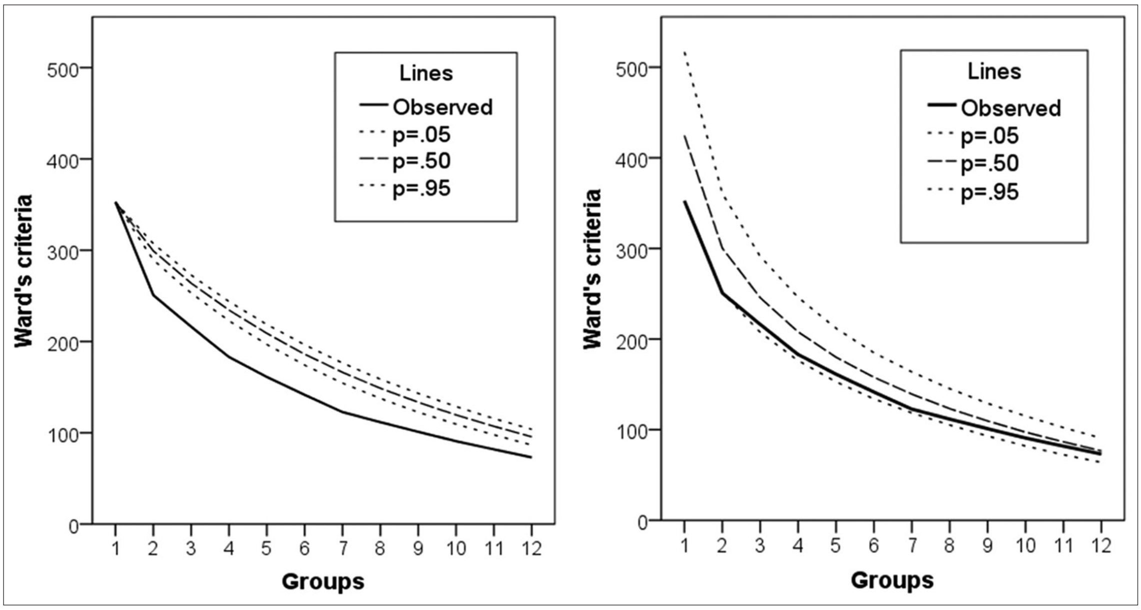

Figure 1: Permutation test (left) and Monte Carlo test (right) for significant clustering

efficiently by using a narrower variety of aircraft. They tend to lease more of their planes, thereby operating with a younger fleet. Finally, low-cost airlines tend to offer only one-way fares, on-line sales channels, and no frequent flier programs.

The easily recognizable patterns on the key strategy variables support the face validity of these two iconic strategic groups, as does the assignment of the specific airlines to each group (see Table 2). What is perhaps more controversial is the increasing speculation among industry experts that there is "a convergence trend in airline business models to the 'mainstream middle'" (Daft and Albers, 2015, p. 3). While the trend might be heading in that direction, significant clustering is still present in the 2012 data, so the *interdependent view* can be used to (a) interpret these findings and (b) select the hypotheses for subsequent tests.

Typically, researchers are trained to ignore any results that are not significant, but for cluster analysis Hatten and Hatten (1987) argue that even in the absence of significance tests, "strategic groups are one of the most valuable analytic concepts in the armory of the strategist, practitioner or researcher" (p. 340-341). The four-cluster solution is significant on the permutation test (p=0.001) but not the Monte Carlo test (p=0.082). While the significance tests do not converge on the four cluster solution, the scree plot of the observed values (the solid line in both plots) reveals a prominent kink or elbow for four groups, which suggests that it is potentially an interesting solution. However, Hatten and Hatten are quite strict in stating that the interpretation of the *groupings* and subsequent hypothesis tests must be limited to the *independent view* in which groupings are merely an analytic convenience. These subgroupings are shown in Table 2 and Figure 2.

Table 2: Strategic groups for the significant 2-group solution (low-cost versus full-service) with additional splits for the nonsignificant 4-group solution

Low-cost airlines	Full-service airlines
Pure low-cost	Large full-service
EasyJet	Air France
Ryanair	Austrian Airlines
Mostly low-cost	British Airways
Aegean Airlines[b]	Iberia
Aer Lingus	KLM
Flybe[b]	Lufthansa
Germanwingsa[b]	Swiss
Monarch Airlines	Small full-service
Norwegian Air Shuttle	Air Berlin[b]
Transavia[a]	Air Europa[a]
Vueling Airlines[b]	Alitalia
	Condor
	Finnair
	SAS Scandinavian Airlines
	TAP Portugal
	Turkish Airlines
	Virgin Atlantic Airways[a]

[a]Missing data for performance measures. [b]Examples of hybridization.

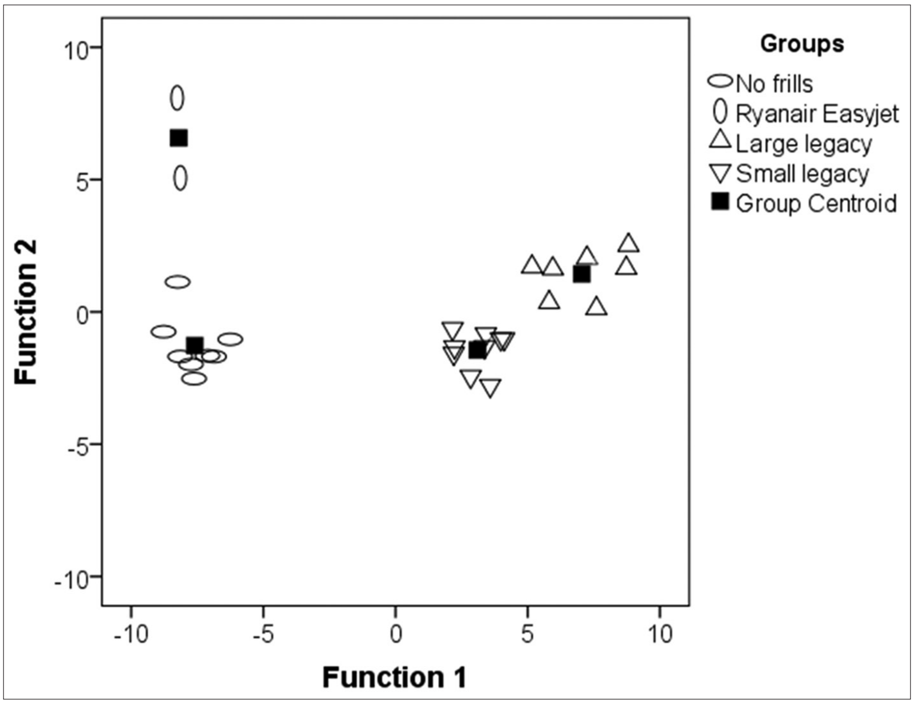

Figure 2: Scatter plot of the 4-cluster solution using canonical discriminant functions to show the clearest separation of groups in the strategy space

The no-frills airlines (indicated by ovals) are subdivided into Ryanair and EasyJet in one group and the rest of the no-frills airlines in the other group. Ryanair and EasyJet embrace the low-cost strategy more fully than their peers who often differentiate slightly on services. The legacy airlines (indicated by triangles) are essentially divided based on size (small versus large). These two groups are close to each other, but the small legacy airlines seem to lean slightly towards the low-cost formula. So, the four-cluster solution reveals that each core strategy (low-cost or full-service) has a group of purists coupled with a group that is leaning slightly in the direction of the opposing business model. The airlines that Daft and Albers (2015) used to illustrate the

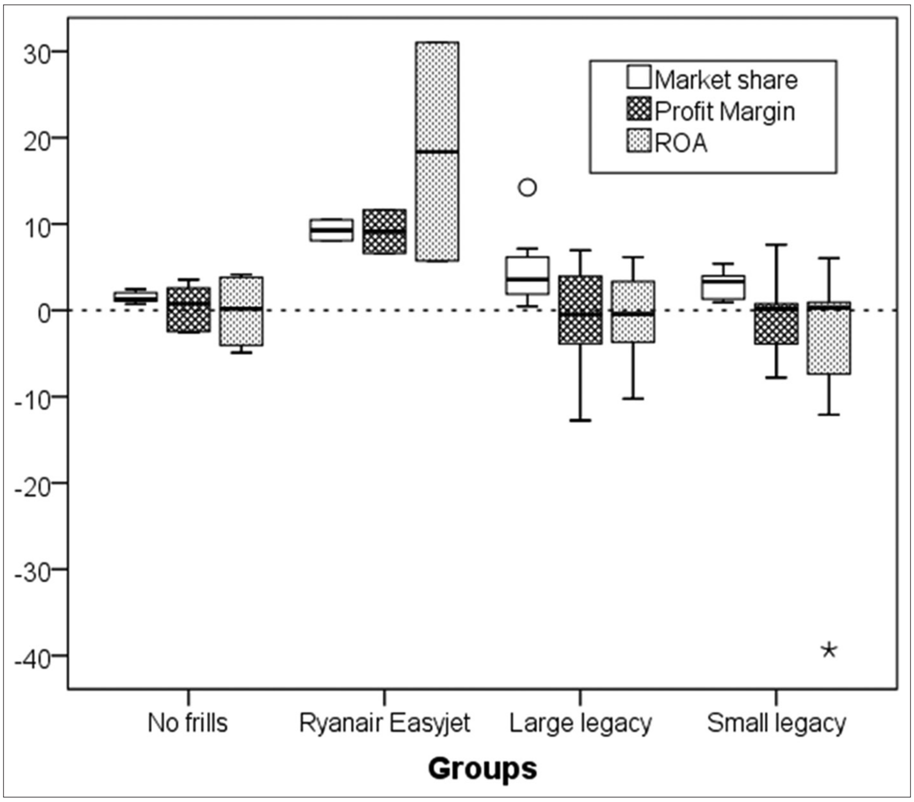

Figure 3: Distribution of performance measures for each group in the 4-cluster solution

shift towards the mainstream middle are included in these hybrid groups (see note *b* in Table 2). Again, this supports the face validity of the results.

5.2. Performance Differences Across Groups

The tests for significant clustering do not indicate whether or not performance differences *must* exist across groups, but they do provide information regarding the structure of the industry (smooth or clumpy) that can be used to deduce when true group-effects on performance are *possible*. In Figure 2, the distance between the two significant groups (the ovals versus the triangles) is relatively large indicating that the groups are following distinctly different strategies, making it unlikely that the low-cost airlines would respond directly to actions taken by the full-service airlines, and vice versa (Porter, 1979; Cool and Schendel, 1988).

If competitive reactions are contained within each group, then the conduct within the groups can differ. Consequently, true group-effects could yield differences in performance across groups. However, both clusters have enough members to make collusive arrangements within each cluster difficult to establish and maintain. Further, exogenous shocks like fluctuations in oil prices force airlines to change their prices in order to pass the costs or savings on to their customers. Frequent changes increase the risk of misunderstandings, and that can cause the implicit agreements regarding pricing strategies to breakdown. Given these structural considerations, the feasibility of maintaining collusion is low, and both groups will probably lean towards perfect competition. Consequently, their performance should be roughly equal.

Theoretically, differences due to true group-effects (associated with the interdependent view) have been ruled out, but it is still possible that aggregate differences due to firm-level effects could exist. A MANOVA was run on the two-group solution, but there were no significant differences across groups. Similarly, separate ANOVAs for market share, profit margin, and ROA were also nonsignificant.

Turning to the four-group solution, the degree of clustering was not significant, so true group-effects are theoretically not possible. Still, Hatten and Hatten (1987) (the champions of the independent view) argue that aggregating the firm-level effects for each grouping could shed light on profitability of each strategy (see Figure 3). Only the ANOVA for market share was significant (F=4.111, p=0.022), and the only significant difference between groups was the mean market share for the Ryanair-EasyJet group was higher than that for the other no-frills airlines (Tukey's HSD, p=0.021). Note that the variance within groups is small for market share compared to the other performance indicators. This seems to washout the differences between groups on those measures (McNamara, Deephouse and Luce, 2003).

Since the four-cluster solution is not significant, these results must be interpreted within the *independent* view that considers firm-level effects associated with the strategic position, but rules out any consideration of effects associated with interactions within a particular group. It appears that airlines following a pure low-cost strategy (Ryanair and EasyJet) have a *firm-level* advantage allowing them to offer lower prices to customers and capture more market share compared to airlines that have differentiated slightly from that low-cost formula.

6. DISCUSSION

This analysis of the European airline industry illustrates the value of a multimethod approach. Since the weaknesses of the two significance tests do not overlap, their convergence on the two-cluster solution provides greater confidence that there are two distinct strategic groups in this industry.

However, the complementarity of the two tests goes deeper than simply having non-overlapping sets of weaknesses. The Monte Carlo test can be seen as a validity check for the permutation test in that it explicitly rules out one of the key threats to its validity. A significant result on a permutation test could be due to (a) clustered observations (which tend to cause correlations among variables) or (b) correlations among variables in the absence of clustering (the key weakness for this test). The Monte Carlo test generates a null distribution of the clustering statistic under the latter condition. If the Monte Carlo test is significant, that means that it is unlikely that the result was generated by correlations in the absence of clustering. This bolsters the confidence (but cannot *prove*) that the permutation test is actually picking up patterns of clustering.

Another major implication of this airline example is that the two-cluster solution which was significant on both tests captures two easily recognizable strategic groups: low-cost airlines and full-service airlines. This provides support for the face validity of the clusters. These groups epitomize the epic battle between opposing generic strategies: cost leadership and differentiation (Porter, 1980). The interdependent view of strategic groups correctly predicted that there would be no true group-effects because the size of the groups and the turbulent nature of the industry would make it difficult to maintain collusive agreements. The lack of aggregate differences across groups is also consistent with equifinality regarding firm-level performance (Katz and Kahn, 1978; Marlin, Ketchen, and Lamont, 2007). This finding is consistent with "the highly competitive and notoriously unprofitable airline industry" (Daft and Albers, 2015, p. 3). As Richard Branson (n.d.) famously put it, "If you want to be a millionaire, start with a billion dollars and launch a new airline."

The group membership-performance link has been used to conclude that the lack of performance differences implies that strategic groups (in the interdependent view) do not exist or that they are inherently uninteresting. However, it is common knowledge that the two strategic groups in this example (no-frills and full-service airlines) do indeed exist, and they are engaged in an enthralling battle. While the group membership-performance link is often used to challenge the validity of the concept of strategic groups, the findings in this example combined with decades of empirical results support a far more compelling argument that it is the group membership-performance link that is invalid—at least as it has been applied in strategic groups research.

Another implication from this example is that interesting insights can be gained from a strategic groups analysis even if significant clustering is not found. Hatten and Hatten (1987) rightly argue that even if strategic groups are only used as an analytical convenience (the independent view), they can still be illuminating. For instance, the four-cluster solution was not significant, so true group-effects are ruled out. Yet, aggregate statistics for these groupings still identified interesting firm-level effects. Ryanair and EasyJet appear to share the position as low-cost leaders, and the rest of the no-frills airlines are trying to differentiate slightly from that position to avoid competing directly on price. The use of point-to-point routes (rather than hub-and-spoke) might allow Ryanair and EasyJet to divide the market geographically to avoid competing on the same routes. Thus, the feasibility of collusion might increase in the future if the vaguely low-cost airlines continue to differentiate themselves from the pure low-cost formula and migrate further towards the mainstream middle.

The convergence on the mainstream middle predicated by Daft and Albers (2015) could provide a natural experiment in which fuzzy techniques could show their worth. The significance tests presented here determine if distinct, relatively isolated groups exist. However, if the degree of clustering is not significant, then *fuzzy c-means clustering* (Liang, Chou and Han, 2005; Budayan, Dikmen, Birgonul, 2009), *fuzzy sets* (fs/QCA) (Ragin, 1987, 2000) or a *multiobjective NORMCLUS* method (DeSarbo and Grewal, 2008) could be used to explore the effects of partially overlapping groups on the spread of competitive (re)actions between those groups. It would also be particularly interesting to study the role that the firms in hybrid positions play in the diffusion of competitive behaviours across groups.

7. CONCLUSION

The field of strategic groups research offers enormous potential for exploring the social structure of rivalry within an industry, but it has lost momentum in the recent decades. I attribute the current malaise to the unfortunate coevolution of the conceptualization and operationalization of strategic groups. The lack of a significance test for cluster analysis forced a series of suboptimal theoretical and methodological choices. Fortunately, the recent flurry of interest in computationally intensive tests for significant clustering offers a promising way to move the field forward. In particular, the proposed multimethod approach provides a means to identify strategic groups (in the interdependent view) that is not based on (a) *conflating* the closely related, but theoretically distinct concepts of strategic groups and mobility barriers or (b) *confounding* the effects of strategic groups with those of countless other variables.

The advent of significance tests can be used in the traditional *exploratory* manner to determine if the sample at hand conforms to the independent or the interdependent view of strategic groups. That is, do the identified clusters represent groupings of similar firms as an analytic convenience or do they constitute coherent groups of interdependent, interacting firms? Further, these significance tests can foster theory development in an *explanatory* manner by testing hypotheses regarding the formation of strategic groups. For example, population ecology or neo-institutionalism could be used to generate hypotheses regarding the conditions conducive to the emergence of strategic groups. That is, what would cause rival firms to clump together? The multimethod approach proposed here could then be used to test those hypotheses. Hopefully, these developments in both the conceptualization and the operationalization will help usher in a resurgence in strategic groups research.

REFERENCES

Anand, V., Joshi, M., & O'Leary-Kelly, A. M. (2013). An organizational identity approach to strategic groups. *Organization Science*, *24*(2), 571-590.

Baird, I. S., Sudharshan, D., & Thomas, H. (1988). Addressing temporal change in strategic groups analysis: A three-mode factor analysis approach. *Journal of Management, 14*(3), 425-439.

Barney, J. B., & Hoskisson, R. E. (1990). Strategic groups: Untested assertions and research proposals. *Managerial & Decision Economics, 11*, 187-198.

Branson, R. (n. d.). Retrieved February 25, 2017, from https://www. brainyquote. com/quotes/quotes/r/richardbra452106. html

Brewer, J., & Hunter, A. (2006). *Foundations of multimethod research: Synthesizing styles.* Thousand Oaks, CA: SAGE Publications.

Budayan, C., Dikmen, I., & Birgonul, M. T. (2009). Comparing the performance of traditional cluster analysis, self-organizing maps and fuzzy C-means method for strategic grouping. *Expert Systems with Applications*, *36*, 11772–11781.

Cattani, G., Porac, J. F., & Thomas, H. (2017). Categories and competition. *Strategic Management Journal*, *38*, 64–92.

Clarke, K. R., & Gorley, R. N. (2015). *PRIMER v7: User manual/tutorial*. Plymouth, UK: PRIMER-E.

Clarke, K. R., Somerfield, P. J., & Gorley R. N. (2008). Testing of null hypothesis in exploratory community analyses: Similarity profiles and biota-environment linkage. *Journal of Experimental Marine Biology and Ecology*, *366,* 56–69.

Cool, K., & Schendel, D. (1988). Performance differences among strategic group members. *Strategic Management Journal*, *9*(3), 207-223.

D'Aveni, R. A. (1994). *Hypercompetition: Managing the dynamics of strategic maneuvering.* New York: Free Press.

Daft, J., & Albers, S. (2015). An empirical analysis of airline business model convergence. *Journal of Air Transport Management*, *46*, 3-11.

DeSarbo, W. S., & Grewal, R. (2008). Hybrid strategic groups. *Strategic Management Journal*, *29*(3), 293-317.

Dess, G. G., & Davis, P. S. (1984). Porter's (1980) generic strategies as determinants of strategic group membership and organizational performance. *Academy of Management Journal*, *27*(3), 467-488.

Harrigan, K. R. (1985). An application of clustering for strategic group analysis. *Strategic Management Journal, 6,* 55-73.

Hatten, K. J., & Hatten, M. L. (1987). Strategic groups, asymmetrical mobility barriers and contestability. *Strategic Management Journal*, *8*(4), 329-342.

Hayes, S. L. III, Spence, A. M., & Marks, D. V. P. (1983). *Competition in the investment banking industry.* Cambridge, MA: Harvard University Press.

Hunt, M. S. (1972). *Competition in the major home appliance industry, 1960-1970*. Unpublished doctoral dissertation, Harvard University.

Jones, D. L. (2015). Fathom toolbox for Matlab: Software for multivariate ecological and oceanographic data analysis. Retrieved August 15, 2015, from http://www. marine. usf. edu/user/djones/

Katz, D., & Kahn, R. L. (1978). *The Social Psychology of Organizations*. New York: Wiley.

Ketchen, D. J., Jr., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: An analysis and critique. *Strategic Management Journal*, *17*(6), 441-458.

Kim, L., & Lim, Y. (1988). Environment, generic strategies, and performance in a rapidly developing country: A taxonomic approach. *Academy of Management Journal*, *31*(4), 802-827.

Liang, G.-S., Chou, T.-Y., Han, T.-C. (2005). Cluster analysis based on fuzzy equivalence relation. *European Journal of Operational Research, 166*, 160–171.

Marlin, D., Ketchen, D. J., Jr., & Lamont, B. (2007). Equifinality and the strategic groups — performance relationship. *Journal of Managerial Issues*, *19*(2), 208-232.

McGee, J., & Thomas, H. (1986). Strategic groups: Theory, research and taxonomy. *Strategic Management Journal*, *7*(2), 141-160.

McKelvey, B. (1982). *Organizational systematics: Taxonomy, evolution, classification.* Berkeley: University of California Press.

McNamara, G. M., Deephouse, D. L., & Luce, R. A. (2003). Competitive positioning within and across a strategic group structure: The performance of core, secondary and solitary firms. *Strategic Management Journal, 24*(2): 161-181.

Meyer, A. D. (1991). What is strategy's distinctive competence? *Journal of Management*, *17*(4), 821-833.

Miles, R. E., & Snow, C. C. (1978). *Organizational strategy, structure and processes*. New York: McGraw-Hill.

Newman, H. H. (1973). *Strategic groups and the structure/performance relationship: A study with respect to the chemical process industries.* Unpublished doctoral dissertation, Harvard University.

Parnell, J. A., & Wright, P. (1993). Generic strategy and performance: An empirical test of the Miles and Snow typology. *British Journal of Management*, *4*, 29-36.

Pegels, C. C., & Sekar, C. (1989). Determining strategic groups using multidimensional scaling. *Interfaces*, *19*(3), 47-57.

Porter, M. E. (1979). The structure within industries and companies' performance. *Review of Economics and Statistics*, *61*(2), 214–227.

Porter, M. E. (1980). *Competitive strategy*. New York: Free Press.

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *68*(2), 73-93.

Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies.* Oakland, CA: University of California Press.

Ragin, C. C. (2000). *Fuzzy-set social science*. Chicago, IL: Univ. of Chicago Press.

Serrano-Cinca, C. (1998). From financial information to strategic groups: A self-organizing neural network approach. *Journal of Forecasting*, *17*, 415-428.

Tang, M.-J., & Thomas, H. (1992). The concept of strategic groups: Theoretical construct or analytical convenience. *Managerial and Decision Economics*, *13*(4), 323-329.

Whitaker, D., & Christman, M. (2014). *Clustsig: Significant cluster analysis*. Retrieved August 15, 2015, from https://cran.rproject.org/web/packages/clustsig/index.html Appendix Appendix Appendix

APPENDIX

Appendix: trategy variables taken from daft and albers (2015) with modifications for clustering

No.	Item	Recoded or combined for cluster analysis
2	Basic route design	0=point-to-point variations; 1=hub & spoke
3	Spatial scope	z-score
7	Aircraft utilization	z-score
10	cooperative agreements	sum: 1(if code share) + 1(if alliance) + 1(if JV)
11	Target passenger groups	number of service classes
12	Role of air cargo	ordinal
17	Routes offered	z-score
20	In-flight entertainment (IFE)	ordinal
23	Online distribution	ordinal
25	One-way fares	ordinal
26	Bundling concept	sum: 1 (if baggage) + 1 (if catering)
28	Sales promotion	ordinal
29	Fleet uniformity	z-score
30	Fleet modernity	z-score
35	Access to primary airports	z-score
new	outsourcing	scale score = mean of five z-scores below
13	Maintenance, repair overhaul	ordinal → z-score
14	Ground services sourcing	ordinal → z-score
33	Human resources develop.	ordinal → z-score
34	Flight crew skills	ordinal → z-score
36	Software for major processes	ordinal → z-score
new	leasing: facilities & aircraft	scale score = mean of two z-scores below
15	Aircraft financing	z-score
32	Owning facilities	reversed ordinal → z-score