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# DYNAMIC STRATEGIC GROUPS: DERIVING SPATIAL EVOLUTIONARY PATHS

WAYNE S. DESARBO,[1]* RAJDEEP GREWAL,[1] and RUI WANG[2]
[1] *Smeal College of Business, Pennsylvania State University, University Park, Pennsylvania, U.S.A.*
[2] *Guanghua School of Management, Peking University, Beijing, People's Republic of China*

*Recent theoretical developments in the domain of strategic groups, specifically those related to cognitive groups and strategic group identity, seem to suggest that strategic group membership is likely to be relatively stable over time and that firms in a strategic group co-evolve. Yet appropriate data analytic approaches that use information about firms over time to identify stable strategic groups and their evolutionary paths have been lacking. To overcome such limitations, this research proposes a new clusterwise bilinear multidimensional scaling model that can simultaneously identify (1) the number of strategic groups, (2) the dimensions on which the strategic groups are based, and (3) the evolution of the strategy of these groups over time. Our discussion encompasses various alternative model specifications, together with model selection heuristics based on statistical information criteria. An illustration of the proposed methodology using data pertaining to strategic variables for a sample of public banks in the tristate area of New York, Ohio, and Pennsylvania across three time periods (1995, 1999, and 2003) identifies two underlying dimensions with five strategic groups that display very different evolutionary paths over time. Post hoc analysis shows pronounced differences in firm performance across the five derived strategic groups. This article concludes with a discussion of the implications of the findings, as well as potential future research directions. John Wiley & Sons, Ltd.* 

## INTRODUCTION

Given the prominence of strategic groups for understanding strategic recipes, competition, and market structure, it comes as no surprise that scholars have devoted significant attention to understanding *strategic group dynamics* (e.g., Cool and Schendel, 1987; Fiegenbaum and Thomas, 1993; Mascarenhas and Aaker, 1989); that is, the study and investigation of strategic groups over time in an industry. In Table 1, we provide a sample of existing empirical research into strategic group dynamics. The focus of this emerging stream of research relates to understanding changes in strategic group strategy, strategic group membership, and/or the number of strategic groups over time (Mascarenhas, 1989).

Recently, in response to criticisms levied by Barney and Hoskisson (1990) and Hatten and Hatten (1987), among others, scholars have begun to recognize that managerial cognitions about competition and competitors may drive the formation and perpetuation of strategic groups (e.g., McNamara, Deephouse, and Luce, 2003; Porac and Thomas, 1990; Reger and Huff, 1993). Building on organizational identity literature (e.g., Ashforth

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*Correspondence to: Wayne S. DeSarbo, Marketing Department, Smeal College of Business, 433 Business Building, University Park, PA 16802, U.S.A. E-mail: wsd6@psu.edu

Table 1. Synopsis of dynamics in empirical strategic groups literature[a]

| Reference | Industrial context and sample | Analysis time interval | Data analytic technique | Key findings on dynamics |
|---|---|---|---|---|
| Cool and Schendel, 1987 | U.S. pharmaceutical sector, 1963–82, 22 firms. | Data pooled based on homogeneity of covariance structures. | (1) Bartlett's test for homogeneity of covariance structures, (2) cluster analysis (error sum of squares algorithm) to determine strategic groups, (3) ANOVA to explain ifferences in strategic groups. | For the 20-year period, only four subperiods (1963–69, 1970–74, 1975–79, 1980–82) with some differences in strategic group structure are identified; the authors conclude strategic groups are relatively stable phenomena. |
| Fiegenbaum *et al.*, 1987 | U.S. pharmaceutical sector, 1963–82, 22 firms. | Data pooled based on homogeneity of mean structure and covariance structure. | (1) Hotelling's $T^2$ test for homogeneity of mean vectors, (2) Bartlett's test for homogeneity of covariance structures, and (3) cluster analysis to identify strategic groups. | Three stable subperiods (1974–76, 1977–79, 1980–81) for covariance structure and one stable time period for mean vectors. The authors recommend using the concept of stable time periods while studying strategic groups. |
| Mascarenhas and Aaker, 1989 | Oil-drilling industry, 1973–81, 33 firms | Annual, data averaged over time | (1) Cluster analysis to identify strategic groups and (2) discriminant analysis to explain intergroup differences | The three strategic groups identified exhibit group membership stability over time and differences in profitability. |
| Mascarenhas, 1989 | International offshore drilling firms, 1966–84; 1966 (41 firms), 1973 (49 firms), 1981 (110 firms), 1984 (123 firms). | Only compare the variables for firms in four years (1966, 1973, 1981, and 1984). Data treated as independent over time. | (1) Nonhierarchical cluster analyses to identify strategic groups for each of the four years (2) Tukey's test to explain intergroup differences. | Changes in strategy group emphases over time are associated with substantial environmental shifts (growth or decline). These changes are limited to a few dimensions. |
| Fiegenbaum and Thomas, 1990 | Insurance industry, 1970–84, 33 firms. | Data pooled based on homogeneity of mean structure and covariance structure. | (1) Hotelling's $T^2$ test for homogeneity of mean vectors, (2) Bartlett's test for homogeneity of covariance structures, (3) cluster analysis to identify strategic groups, and (4) MANOVA to explain differences across strategic groups. | The empirical findings demonstrate that some performance differences exist among strategic groups (ranging from 3–9 based on time period; 9 time periods). The structure of strategic groups (both in terms of the number and the membership) changes over time. |



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|---|---|---|---|---|
| Fiegenbaum and Thomas, 1995 | The U.S. insurance industry 1970–84, 33 firms; 85 firms for 1970–75 | Annual, with 1983–84 data as hold out. | (1) Hotelling's $T^2$ test for homogeneity of mean vectors, (2) Bartlett's test for homogeneity of covariance structures, and (3) cluster analysis to identify strategic groups. | Strategic groups serve as reference points for competitive strategy with nature of competition varying across strategic groups. Strategic groups also vary in terms of their evolutionary paths. |
| Más Ruíz, 1999 | Spanish banking industry, 1984–91, 24 banks in 1984 and 22 banks in 1991. | Data averaged in 4 subperiods (1984; 1985–86; 1987–88; 1989–91). | (1) Stable time periods identified by homogeneity of mean vector and covariance matrices, (2) cluster analysis to identify strategic groups, and (3) ANOVA to explain intergroup differences. | The structure of the strategic groups changes over the years in terms of their number, composition, and strategy. |
| Osborne *et al*., 2001 | U.S. pharmaceutical, 1963–82, 22 firms. | Four subperiods (1963–69, 1970–74, 1975–79, 1980–82). | (1) Content analysis to assess managerial mental models (2) factor analysis to identify underlying themes, and (3) cluster analysis to identify strategic groups. | Managerial mental models can help explain future performance differences across strategic groups. |
| Kim and Lee, 2002 | Korean electronic parts industry, 1990–95, 115 firms. | Data averaged for two periods, 1990–92 and 1993–95. | (1) Factor analysis to identify underlying dimensions, (2) cluster analysis to identify strategic groups, and (3) ANOVA to explain intergroup differences. | There exists a close association between firms' strategic evolutionary paths (based on evolution of strategic groups) and their technological learning processes. |
| Athanassopoulos, 2003 | U.K. grocery industry, 1987–93, 28 to 35 firms. | Data averaged for 5 SSTPs: 1987; 1988–90; 1991; 1991; 1993. | (1) Bartlett's and Hotelling's $T^2$ test to for homogeneity in covariance and mean structures, respectively, (2) cluster analysis to identify strategic groups, and (3) MANOVA and Kruskal-Wallis's test to explain intergroup difference. | Of the four strategic groups identified, three are stable over time, while the fourth is volatile in terms of membership. |
| Zuniga-Vicente *et al*., 2004 | Spanish banks, 1983–97, 92–103 firms. | Annual. | (1) Box's M test and Hotelling's $T^2$ test to verify homogeneity of covariance and mean structures, (2) cluster analysis to identify strategic groups. | Strategic stability exists at group level and firm level, punctuated by a high degree of strategic instability during times of major environmental disturbances. |

(*continued overleaf*)

| Reference | Industrial context and sample | Analysis time interval | Data analytic technique | Key findings on dynamics |
|---|---|---|---|---|
| Zuniga-Vicente *et al*., 2004 | Private Spanish banks, 1983–97, 136 firms. | Annual. | (1) Box's M test and Hotelling's $T^2$ test to verify homogeneity of covariance and mean structures, (2) cluster analysis to identify strategic groups. | Performance differences across strategic groups are stable over time. |
| Baird *et al*., 1988[b] | Office equipment and electronic computing industry, 1977–81, 46 firms. | Annual. | Three-mode factor analysis (i.e., firms, variables, and time periods) to identify strategic groups. | The number of strategic groups identified depends on the model of factor analysis. *Post hoc* reconciliation reveals six strategic groups. |
| Wiggins and Ruefli, 1995[b] | Five industries previously studied in strategic groups research. | Five-year window. | (1) Nonparametric Kolmogorov-Smirnov two-sample test to identify strategic groups and (2) discriminant analysis to explain intergroup differences. | Strategic group membership is not stable over time. |
| Fiegenbaum *et al*., 2001[b] | Insurance industry, 1970–84, 33 firms. | Annual. | (1) Hotelling's $T^2$ test for homogeneity of mean vectors, (2) Bartlett's test for homogeneity of covariance structures, (3) cluster analysis to identify strategic groups, and (4) Markov process modeling to explain changes in group membership over time. | Few changes in strategic group membership in the short run. Greater number of changes in strategic group membership in the long run. |
| Nair and Filer, 2003[b] | Japanese steel industry, 1980–99, 8 firms. | Annual. | Cointegration analysis with vector error correction to understand long-term competitive dynamics. | Firms slowly adjust their strategies over time. Strategic groups level and firm level differences existed in response to 'shocks.' |

[a] We only describe studies that use some data analytic technique to derive strategic groups over time. We exclude those that rely on researcher judgment and study dynamics according to an *a priori* classification (e.g., Tremblay, 1985, who studies competitive dynamics between national and regional breweries). We also exclude studies that have dynamic data but do not study strategic group dynamics (e.g., Cool and Schendel, 1988; Lewis and Thomas, 1990, who are interested in performance differences across strategic groups).
[b] Studies that deviate from standard multistep methodology.

and Mael, 1989) and categorization research (e.g., Rosch, 1978), Peteraf and Shanley (1997) propose strategic group identity theory, which suggests that strategic groups in an industry have distinctive characteristics, that these groups endure, and that firms within them *co-evolve*. Testing this theory and the notion of the evolution of strategic groups requires modeling approaches that can identify the number of strategic groups, the dimensions on which the strategic groups are based, and the evolution of the strategy of these groups over time. Yet, data analytic approaches to model the evolutionary paths of these strategic groups have been lacking, a gap we attempt to resolve in this manuscript.

Traditionally, empirical studies of strategic group dynamics separately identify stable strategic time periods using tests for the homogeneity of mean vectors and covariance structures (e.g., Fiegenbaum, Sudharshan, and Thomas, 1987), resort to factor analysis to identify underlying dimensions (e.g., Osborne, Stubbart, and Ramaprasad, 2001), and then use cluster analysis to identify strategic groups (e.g., Cool and Schendel, 1987). In Table 1, we organize these studies on the basis of the data analytic approaches they undertake. With the exception of the last four studies, they fall into this genre of multiple independent analyses according to some combination of the three steps: (1) tests of homogeneity, (2) data reduction, and (3) clustering.

However, these multistep processes suffer several limitations as has been well documented in classification and methodology literature (e.g., DeSarbo *et al*., 1991), and strategic management literature (e.g., Ketchen and Shook, 1996). These limitations include the presence of multiple errors that result in statistically inefficient estimates; the optimization of different objective functions by cluster analysis and factor analysis (and some forms of cluster analysis optimize nothing); the likelihood that the smaller factors derived in factor analysis, which are typically discarded, may contain the most relevant clustering information; the problem of several different forms of factor and cluster analyses that typically provide different results with the same set of data; and so on.

Among the exceptions (i.e., last four studies in Table 1), Wiggins and Ruefli (1995) focus on performance groups, rather than strategic groups, and use nonparametric techniques, but they still employ a multistep approach. Fiegenbaum, Thomas, and Tang (2001) also use a multistep approach, but they add a Markov process to account for firm switching between strategic groups. Nair and Filer (2003) attempt a unique methodology that relies on recent cointegration advances in time series analysis to examine firm behaviors within strategic groups, without considering the issue of the evolution of strategic groups. Finally, Baird, Sudharshan, and Thomas (1988) use three-mode factor analysis to 'capture[s] the systematic variance of the firms' scores on financial variables as well as the systematic variance of the same variables over time (Baird *et al*., 1988: 426). However, this spatial methodology cannot provide a simultaneous classification of firms into strategic groups.

We instead propose a new spatial clusterwise multidimensional scaling (MDS) technique that *simultaneously* (1) identifies the number of strategic groups and respective strategic group membership, (2) derives the underlying dimensions on which the strategic groups are based, and (3) models the paths of evolution of the derived strategic groups over time. For this purpose, we devise a deterministic, nonparametric, clusterwise MDS procedure to analyze the three-way strategy data using a spatial, bilinear, scalar products-based vector representation. This approach does not require parametric assumptions, as do latent class MDS procedures. The three-way (firms $\times$ variables $\times$ time) dynamic case prompts a 'floating vector model' spatial representation that enables strategic group vectors to vary on the third factor (here, time). Therefore, we conceive of a concise spatial representation of the analysis of dynamic strategic groups.

The next section provides a conceptual background and technical description of the proposed clusterwise bilinear spatial methodology, as well as an efficient alternating least-squares estimation procedure (technical details are available on request from the authors), which offers *conditional* globally optimum results within an iteration. We then discuss a variety of alternative model specifications to test static versus dynamic representations, overlapping versus nonoverlapping strategic groups (see DeSarbo and Grewal, 2008), and options for external analyses that include strategic groups fixed *a priori* or those developed from managerial cognitions. We also provide model selection heuristics based on well-developed statistical information criteria that guide the selection of the dimensionality, number of strategic groups, and optimal model representation. We apply the proposed methodology to strategic variables for various public banks in the New York, Ohio, Pennsylvania (NY-OH-PA) area during 1995, 1999, and 2003. Finally, we present the derived spatial maps to explain the evolution of strategic groups and discuss the implications of this research, as well as potential extensions of the proposed model for further research.

## CONCEPTUAL FRAMEWORK AND PROPOSED METHODOLOGY

Strategic group identity represents 'a set of mutual understandings, among members of a cognitive intraindustry group, regarding the central, enduring, and distinctive characteristics of the group' (Peteraf and Shanley, 1997: 166). Peteraf and Shanley (1997) emphasize the subtle difference between the mutual understanding that underlies strategic group identity and the shared understanding that underpins organizational identity (Ashforth and Mael, 1989); mutual understanding develops 'through history, discourse, and interactions' among members of a strategic group (Peteraf and Shanley, 1997: 167). Thus, firms in a group can roughly predict one another's reaction functions (Fudenberg and Tirole, 1991). This mutual understanding implies that the central characteristics of a group are enduring and distinctive from those of other strategic groups.

Building on this literature that provides the theoretical basis for strategic groups, we propose that firms in a strategic group use similar sets of strategies to adapt to environmental changes. Specifically, due to their mutual understanding and the institutionalization of cognitive beliefs, firms in a strategic group watch and mimic one another more closely than do firms across different strategic groups (e.g., Porac, Thomas, and Baden-Fuller, 1989; Reger and Huff, 1993). Consequently, isomorphic cognitions and behaviors should become manifest (DiMaggio and Powell, 1983), and the firms in a strategic group should co-evolve as a group. In other words, firms in a strategic group should have similar evolutionary paths. The study of such evolutionary paths requires data analytic approaches that can identify the number of strategic groups, the dimensions on which these strategic groups are based, and the evolution of the strategy of these strategic groups over time. We believe that appropriate data analytic techniques for studying such strategic group dynamics do not currently exist; we therefore make a case to support this conclusion and propose a new technique for remedying the problem.

### Strategic groups and MDS

Strategic group research traditionally relies on factor analysis to identify the underlying dimensions (e.g., Kim and Lee, 2002), and then uses cluster analysis to identify the strategic groups (e.g., Harrigan, 1985). Clusterwise MDS enables modelers to accomplish these two objectives in a single step. With a few exception (e.g., DeSarbo *et al.*, 1991; Flavin, Haberberg, and Polo, 1999; Serrano-Cinca, Mar Molinero, and Queiroz, 2003), MDS has not been used extensively to examine strategic groups. (One of the key criticisms of strategic group research has been its limited emphasis on methodology development.) As DeSarbo *et al.* (1991), Ketchen and Shook (1996), and others document, cluster analysis has several weaknesses: the lack of any theoretical basis for selecting a particular clustering method; the results being contingent on the specific clustering method selected; and the different results obtained using different methodological decisions such as the choice of distance metric, the definition of clusters, and so forth. Using a naïve two-step approach—first conducting a factor analysis and then using cluster analysis to group the resulting factor scores—is fraught with methodological difficulties (cf. Vichi and Kiers, 2001). Each procedure optimizes a different loss function, and different results emerge depending on the type of factor analysis and/or cluster analysis employed (and furthermore, there is no adequate strategic group theory to dictate which selections should be used *a priori*). Finally, as noted in psychometric and classification literature (for citations, see DeSarbo, Manrai, and Manrai, 1994), the minor factors extracted in the first step often get discarded for data reduction purposes, even though those factors often contain the most information about the clusters or groupings in the data.

In the study of dynamics, independent period analysis often occurs after the modeler identifies stable strategic time periods (e.g., Cool and Schendel, 1987; Fiegenbaum *et al.*, 1987). This



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approach results in unnecessary inflation of sample size because the dependent observations (i.e., firm over time) are treated as independent. Because prior states (e.g., strategic group membership in previous periods) are not modeled explicitly, this approach increases the likelihood of finding dynamics when they do not exist, and it is more susceptible to statistical noise than to any concrete change (e.g., Borgatti and Everett, 1997). Procedures based on pooling data over subsequent time periods according to covariance tests ignore first moment (mean) conditions. Finally, an excessive number of parameters are typically estimated in such independent analyses, including the factors/dimensions and classifications per time period. They offer no guarantee of contiguity or connection between periods, because separate dimensional spaces, numbers of strategic groups, and the composition of strategic groups typically are estimated per period of analysis. Finally, these analyses often are influenced by the *ad hoc* decisions that the analyst must make with regard to preprocessing, type of model/software, rotations utilized, and so on.

Our proposed new clusterwise MDS procedure offers several advantages over such traditional approaches in that we attempt to estimate a common strategic variable space, as well as a fixed number and composition of strategic groups over time. Our objective therefore is to derive an evolutionary strategy path for each strategic group over time. That is, the strategic groups we estimate are derived on the basis of the particular patterns of change or paths that they evoke with respect to the various strategic variables employed in the spatial analysis. To illustrate this concept, consider the hypothetical joint space map in Figure 1. The proposed procedure estimates the relevant strategic groups, underlying dimensions, and perspective on how the strategic groups and the underlying dimensions relate to the observed variables over time. Figure 1 illustrates a hypothetical solution for J = 10 strategic variables, R = 2 dimensions, T = 3 time periods, and S = 3 strategic groups, where $S_s^t$ indicates the associated vector for the s-th strategic group in the t-th time period, and the letters A–J label the various strategy-related variables. As with other vector MDS models and representations, the direction of the estimated strategic group vector points in the direction of increased emphasis on a strategy for that strategic group. The orthogonal projection of any variable onto the strategic group vector renders a latent strategic value that represents the magnitude of that variable for that strategic group. As we show in Figure 1, the third derived strategic group displays little strategy change by time period, as opposed to strategic groups 1 and 2 whose vectors ‘float’ and span the entire two-dimensional region, thus indicating strong dynamic effects on strategy. Additional strategic groups, dimensions, strategic variables, and/or time periods may necessitate the

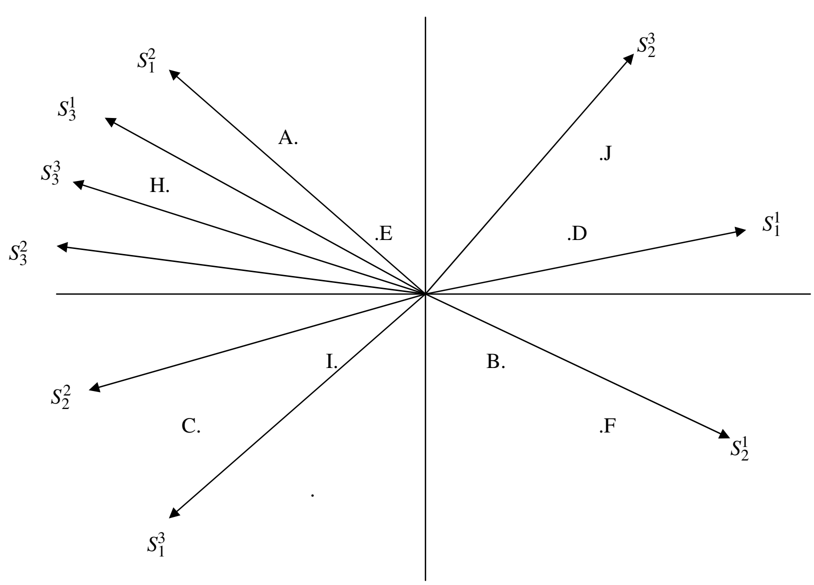


Figure 1. Illustrative derived space for hypothetical data with J = 10, R = 2, T = 3, and S = 3



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construction of separate maps by strategic group to more easily discern specific dynamics.

## The proposed clusterwise MDS model

Let:

i = 1, …, I firms;
j = 1, …, J strategic variables;
t = 1, …, T time periods;
s = 1, …, S clusters or strategic groups (unknown);
r = 1, …, R dimensions (unknown); and
$P_{ijt}$ = the value of strategic variable j for firm i in time t (assumed metric, i.e., interval or ratio scaled).

The general dynamic, three-way model then can be written as:

$$P_{\mathrm{ijt}} = a_t + \sum_{s=1}^{S} \delta_{\mathrm{is}} \sum_{r=1}^{R} W_{rt}\ X_{jr}\ Y_{srt} + \varepsilon_{ijt}, \quad (1)$$

where:
$X_{jr}$ = the r-th coordinate for strategic variable j;
$a_t$ = an additive constant for time t;
$W_{rt}$ = a weight for dimension r for time t;[1]
$Y_{srt}$ = the r-th coordinate for the vector of strategic group s in time t;
$\delta_{is}$ = [ 1 if firm i is a member of strategic group s, and 0 otherwise;
s.t.:

$$\delta_{is} \in \{0, 1\}\ \forall i, s;$$
$$\sum_{s=1}^{S} \delta_{is} = 1\ \forall i; \text{(for partitions) and}$$
$$\varepsilon_{ijt} = \text{error.}$$

The model described in Equation 1 can be viewed as a three-way clusterwise generalization of Carroll's (1980) CANDECOMP model and the two-way clusterwise MDS models proposed by DeSarbo, Grewal, and Scott (2008b) and DeSarbo *et al.* (2008a). By estimating this model, we can derive spatial MDS maps such as that illustrated in Figure 1 to: (1) estimate strategic groups and strategic group membership ($\underline{\delta}$), (2) uncover the underlying dimensions on which the strategic groups are based ($\underline{X}$), and (3) model the strategic evolution of the strategic groups ($\underline{Y}$).

## Estimation procedure

Given $\underline{P}$ and the values of S and R, we estimate $\underline{a}$,$\underline{W}$,$\underline{X}$,$\underline{\delta}$, and $\underline{Y}$ jointly to minimize the following error sums of squares expression:

$$\Phi = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} \left[ P_{ijt} - a_t - \sum_{s=1}^{S} \delta_{is} \sum_{r=1}^{R} W_{rt}\ X_{jr}\ Y_{srt} \right]^2 = \sum_{i,j,t} \varepsilon_{ijt}^2. \quad (2)$$

The numerical details for the alternating least-squares algorithm devised for parameter estimation and a discussion of parameter indeterminacies appear in a technical appendix available upon request from the authors. Each stage of this alternating least-squares procedure provides conditionally global optimum estimates *within* any iteration (but not necessarily globally optimum overall after convergence). In addition, the computational time is reasonable, because all estimating equations are closed-form expressions that do not require time-consuming, gradient-based estimation procedures. The procedure must run for various values of S ≥ R (depending on the model selected as we discuss subsequently), because locally optimum solutions can occur.[2]

Several interesting model variants are possible in this model structure. First, we can modify the procedure to enable the estimation of hybrid strategic groups (DeSarbo and Grewal, 2008), which involves *overlapping strategic groups*. In this case, we would allow the rows of the strategic group membership matrix $\underline{\delta}$ to permit membership in multiple strategic groups, so that the constraint $\sum_{s=1}^{S} \delta_{is} = 1\ \forall i$ is relaxed to $0 < \sum_{s=1}^{S} \delta_{is} \leq S\ \forall i$.

[1] Note: $W_{rt}$ is not identified in the full model presented in Equation 1. It is identified (up to scale transformation) in the nested model where we constrain $Y_{srt} = Y_{sr}$ for all time periods for testing a static model of strategic groups to be discussed shortly.

[2] In response to the concerns about local optimum solutions, using synthetically created data based on the model structure, we performed 100 different runs using different random starting values for the parameter estimates. The results of the 100 runs all fall within 99.5 percent of the globally optimum solution, and the globally optimum solution is recovered in 93 of the 100 runs.



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Second, we can allow for a *stationary representation* of strategic groups (no change in strategy over time, DeSarbo and Grewal, 2008) by constraining $Y_{srt} = Y_{rt}\ \forall s$. Third, we can perform *external analyses* in which $\underline{\delta}$ remains fixed or constant during the estimation process for situations that demand testing of a competing strategic grouping (e.g., from managerial cognitions or perceptions of competition in an industry).

## Model selection heuristics

Several different issues arise involving which model variant best describes the structure in the data. First, how do we select the 'best' value of S (the number of strategic groups)? Second, how do we determine which dimensionality (R) is optimal? Third, what about selecting which model variant is best (e.g., partitions versus overlapping strategic groups, stationary versus dynamic strategic groups)? For such questions, researchers use various information criteria to support their model selection in stochastic specifications involving maximum likelihood estimation (MLE). Although our proposed procedure is deterministic, assuming a normally distributed error term and minimizing the error sums of squares is equivalent to maximizing a concentrated likelihood expression (i.e., least-squares and MLE estimates are identical). Therefore, we can employ an entire family of statistical-based heuristics that involve information measures for the model selection heuristics. Such measures attempt to balance the increase in fit obtained from estimating a larger number of parameters (i.e., more strategic groups or multiple models estimated) with the need for a more parsimonious model that does not estimate unnecessary parameters. Wedel and Kamakura (2000) provide a general form for such information measures (which they call the general information criterion [GIC]):

$$\mathrm{GIC} = -2\ \ln\ \mathrm{L} + \mathrm{Fd}, \tag{3}$$

where F is the number of parameters estimated (minus any scale or rotational indeterminacies), and d is some specified constant. This d constant imposes a penalty on the likelihood that reflects the increase in fit (more parameters yield a higher likelihood) against the number of parameters estimated. The constant d thus attempts to penalize models that have many parameters that do not significantly increase the likelihood. The classical Akaike (1974) information criterion, designated AIC, arises when d = 2. Two other information criteria also penalize the likelihood more heavily for additional parameters to be estimated: the Bayesian information criterion (BIC) (Schwarz, 1978), which occurs when d = ln N, and the consistent Akaike information criterion (CAIC) (Bozdogan, 1987), which forms in Equation 3 when d = ln (N) +1. In all these variants, the model solution with the lowest GIC measure is the one selected (for a discussion of other model selection heuristics, see Burnham and Anderson, 2002). Both BIC and CAIC impose an additional sample size penalty on the likelihood and tend to be more conservative than the AIC in favoring more parsimonious models (i.e., model solutions with fewer strategic groups and/or dimensions); they also tend to result in similar model selections. When there is reason to believe that the true model is included in the set, BIC may be preferable because of its consistency properties (Kuha, 2004), as it outperforms AIC (McQuarrie and Tsai, 1998; Rust *et al.*, 1995). Yang and Yang (2007) also find that AIC decreases the average accuracy rates as sample sizes increase. Therefore, we use BIC and CAIC for model selection, and we calculate an adjusted $R^2$ statistic that adjusts the fit to the number of parameters in the estimated model.

# AN APPLICATION TO DYNAMIC STRATEGIC GROUPS

## Strategic groups in banking

We illustrate this proposed methodology for the public banking industry. Because of its strategic and economic significance, banking has served as a research context for a host of strategic group studies (e.g., Amel and Rhoades, 1988; DeSarbo and Grewal, 2008; McNamara *et al.*, 2003; Mehra, 1996; Más Ruíz, 1999; Serrano-Cinca, 1998; Zuniga-Vicente, Fuente-Sabate, and Rodriguez-Puerta, 2004). Furthermore, the banking sector represents a turbulent environment with fuzzy boundaries, so identifying its strategic groups is a nontrivial problem (Amel and Rhoades, 1992; Fiegenbaum and Thomas, 1993). To study strategic groups longitudinally in banks, it makes sense to use archival data because governmental regulations make a host of secondary data readily available, and these data go beyond the financial strategy of the bank (e.g., liquidity and leverage ratios) to incorporate two primary product portfolios: loans and deposits (e.g., Amel and Rhoades, 1988; McNamara *et al.*, 2003; Mehra, 1996). We collected archival data from the COMPUSTAT database for the years 1995, 1999, and 2003 in the tristate region of NY-OH-PA. This period includes the Gramm-Leach-Bliley Act (12 November 1999), which opened competition among banks, securities companies, and insurance companies. In addition, a comparison of the mean vectors using Hotelling $T^2$ tests and covariance matrices using the Bartlett test shows statistically significant differences in the 1995/1999 comparisons and the 1999/2003 comparisons.

### Variable batteries

Although the constructs and variables used to derive strategic groups vary with the industry contexts and research objectives (e.g., Ketchen, Thomas, and Snow, 1993; McGee and Thomas, 1986; Thomas and Venkatraman, 1988), researchers typically focus on strategic variables (e.g., Frazier and Howell, 1983; Harrigan, 1985; Lewis and Thomas, 1990) that emanate from the basic definition of strategic groups. That is, firms within strategic groups follow similar strategic recipes, whereas firms across strategic groups differ in their strategic emphasis (e.g., McGee and Thomas, 1986). Specifically, and in line with research in finance (e.g., Brealey and Myers, 1988) and strategic groups (e.g., Baird *et al.*, 1988), we use leverage and liquidity ratios, such as current and debt-to-equity ratios, respectively, to assess the financial strategy; we use loans and deposits to reflect the product strategy (e.g., Rose, 1999; see also DeSarbo and Grewal, 2008). To profile the derived strategic groups, we employ five variable categories: (1) market value ratios, (2) efficiency ratios, (3) liquidity and leverage ratios, (4) product portfolio of loans, and (5) product portfolio of deposits. Prior to our analyses, we standardize each variable to 0 mean and constant variance, to account for their different measurement scales.

Although we use only strategic variables to estimate the strategic groups, we also consider *post hoc* performance differences across strategic groups to establish the validity of the groups, according to market- and efficiency-based indicators of firm performance (e.g., DeSarbo and Grewal, 2008; Wiggins and Ruefli, 1995). Market-based indicators such as Tobin's q and the price-to-earnings ratio capture current earnings and future profit potential, along with intangible firm value (e.g., Wernerfelt and Montgomery, 1988); efficiency-based indicators such as return on assets and net profit margins assess the effectiveness of current firm strategies (e.g., Wiggins and Ruefli, 1995).

### Variable operationalization

Traditionally, geographic constraints have driven competition in the banking industry because most customers are unwilling to travel long distances to meet their banking needs; therefore, strategic groups research tends to focus on geographically restricted areas (e.g., DeSarbo and Grewal, 2008; McNamara *et al.*, 2003; Serrano-Cinca, 1998; Zuniga-Vicente *et al.*, 2004). Several bank executives verify this geographically restrictive notion of competition. Our archival data from the COMPUSTAT banks database therefore applies only to the years 1995, 1999, and 2003 for the tristate NY-OH-PA area, which features 64 public banks that remain common across the years of study.[3]

Among the firm strategy variables, we define current ratio as the ratio of current assets to current liabilities, which captures *firm liquidity*; in addition, we use (1) debt-to-equity ratio, (2) total borrowing to total assets, and (3) interest expense to total assets as indicators of the *leverage ratio* (Brealey and Myers, 1988). Regarding the *loans product portfolio*, we consider the ratios of gross loans to total investment securities and gross loans to total assets (Rose, 1999; Más Ruíz, 1999), whereas for the *deposits product portfolio*, we employ four ratios (Rose, 1999; Serrano-Cinca, 1998): (1) total investment securities to total worldwide deposits, (2) gross loans to total worldwide deposits, (3) total borrowings to total worldwide deposits, and (4) total interest expense to total worldwide deposits.

For firm performance variables (which we use not to estimate strategic groups, but rather to establish the *post hoc* validity of the strategic groups),

[3] We used Hoover's Online database to obtain information about the location of the headquarters of banks to identify these 64 banks.



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we consider Tobin's q, market-to-book value, dividend yield, and price-to-earnings ratio for our assessment of *market value* (Brealey and Myers, 1988; Tobin, 1969; Wernerfelt and Montgomery, 1988). We use the approximation detailed by Chung and Pruitt (1994) to operationalize Tobin's q, which often appears in empirical research (e.g., Bharadwaj, Bharadwaj, and Konsynski, 1999; Lee and Grewal, 2004). Our measure of *bank efficiency* includes (1) sales to total assets, (2) net profit margin, (3) return on assets, and (4) sales per employee (Brealey and Myers, 1988). In Table 2, we present the descriptive statistics for these variables (in raw, unstandardized form) pooled over the focal years, and their respective bivariate correlation coefficients. Because the strategic variables have been standardized to 0 mean and constant variance across the three time periods to remove scale/measurement differences, the interpretations of the resulting derived joint spaces must refer to changes above or below the sample averages.

## EMPIRICAL RESULTS

### Model selection

In Table 3, we present the various model selection heuristic values for determining the number of underlying dimensions (R) and the number of strategic groups (S) for the proposed clusterwise MDS expression in Equation 1. Note that we performed this analysis with respect to four different model variants: static versus dynamic representations, and partitions versus overlapping (hybrid) strategic groups. (For parsimony, we reproduce the fit values for the best model in Equation 1, namely, a dynamic model with partitions.) For each run, we performed 10 analyses (i.e., 10 starting values) and selected the best fitting solution for the values of S and R according to the information model selection heuristics. On the basis of the BIC and CAIC values, we select $R = 2$ dimensions and $S = 5$ strategic groups in a dynamic solution with nonoverlapping strategic groups; it is the most parsimonious solution, with a corresponding variance accounted for (VAF) of 0.533 and sum of squares error (SSE) of 896.739, as well as an estimated total of only 53 independent model parameters plus the classifications. This solution offers the lowest values for all information criteria reported in Table 3, as well as the highest adjusted $R^2$ for all four models tested. Therefore, we obtain support for this particular model solution across the various goodness-of-fit measures.

As another comparative benchmark, we compare the fit of this model to one that employs the traditional two-step approach: factor analysis (we used a principal components analysis because of its least-squares optimality properties) followed by cluster analysis (we used K-means because it attempts to create clusters that minimize a SSE criterion). For this same $S = 5$ strategic group and $R = 2$ dimensions, the traditional two-step analyses renders a VAF of 0.195 and SSE of 1544.3—a much worse solution in terms of explaining the data structure. Again, this result illustrates that such disjointed traditional approaches can be truly sub-optimal.

In response to concerns about locally optimum solutions, we ran 100 different analyses of the $S = 5$ strategic groups and $R = 2$ dimensions solution using different random starting values for the parameters with this banking data and dynamic model. All resulting runs fall within 98 percent of the globally optimum solution, and the globally optimum solution appears 80 percent of the time.

### Proposed model joint space solution

In Figure 2, we present the derived clusterwise MDS map for the first strategic group in two dimensions, jointly representing the 10 strategic variables used in this analysis. The top half of the vertical axis represents *borrowings* as total borrowings to total assets, total borrowings to total worldwide deposits, debt-to-equity ratio, and total investment expense to total worldwide deposits load high in this direction on this dimension. The bottom half of the axis represents *liquidity* as the current ratio loads high in this direction on this dimension. The left half of the horizontal axis represents *investments* as total investment securities to total worldwide deposits tends to dominate this dimension. Finally, the right half of this axis, or *product ratio for loans*, involves gross loans to total assets, gross loans to total worldwide securities, and gross loans to total investment securities, which all load high in this direction on this dimension. Note, this two-dimensional strategic variable space ($\underline{X}$) is common across all five derived strategic groups as seen in Figures 2–6.



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Table 2. Descriptive statistics and bivariate correlation coefficients

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tobin's q | | | | | | | | | | | | | | | | | | |
| Market-to-book ratio | 0.49** | | | | | | | | | | | | | | | | | |
| Dividend yield | 0.148* | 0.021 | | | | | | | | | | | | | | | | |
| Price-to-earnings ratio | 0.145* | 0.122 | −0.172* | | | | | | | | | | | | | | | |
| Sales to total assets | −0.090 | 0.142* | 0.093 | −0.135 | | | | | | | | | | | | | | |
| Net profit margin | 0.293** | 0.362** | 0.118 | −0.064 | −0.190** | | | | | | | | | | | | | |
| Return on assets | 0.227** | 0.356** | 0.137 | −0.085 | 0.258** | 0.880** | | | | | | | | | | | | |
| Sales per employee | 0.277** | 0.165* | 0.021 | −.0188** | −0.055 | −0.331** | −0.427** | | | | | | | | | | | |
| Current ratio | −0.119 | −0.127 | −0.041 | 0.048 | 0.109 | 0.346** | 0.383** | −0.198** | | | | | | | | | | |
| Debt-to-equity ratio | 0.682** | −0.011 | 0.117 | −0.021 | −0.210** | −0.180* | −0.254** | 0.399** | −0.488** | | | | | | | | | |
| Total borrowing to total assets | 0.811** | 0.016 | 0.149* | 0.039 | −0.230** | −0.047 | −0.139 | 0.332** | −0.375** | 0.934** | | | | | | | | |
| Interest expense to total assets | −0.158* | −0.368** | 0.043 | −0.184* | 0.332** | −0.523** | −0.328** | 0.186** | −0.189** | 0.242** | 0.134 | | | | | | | |
| Gross loans to total securities | −0.081 | 0.020 | 0.102 | −0.069 | 0.092 | −0.017 | 0.034 | −0.035 | −0.058 | −0.050 | −0.059 | 0.069 | | | | | | |
| Gross loans to total assets | −0.284** | −0.084 | 0.008 | −0.076 | 0.226** | −0.041 | 0.077 | −0.220** | 0.097 | −0.288** | −0.284** | 0.183* | 0.394** | | | | | |
| Total investment securities to total deposits | 0.433** | −0.118 | −0.029 | 0.088 | −0.430** | 0.008 | −0.180* | 0.242** | −0.117 | 0.559** | 0.568** | 0.060 | −0.447** | −0.730** | | | | |
| Gross loans to total deposits | 0.294** | −0.065 | 0.171* | −0.080 | 0.079 | −0.004 | 0.046 | 0.043 | −0.058 | 0.347** | 0.399** | 0.224** | 0.466** | 0.710** | −0.371** | | | |
| Total borrowings to total deposits | 0.769** | −0.035 | 0.140 | 0.013 | −0.239** | −0.038 | −0.137 | 0.345** | −0.338** | 0.930** | 0.975** | 0.153* | −0.059 | −0.334** | 0.626** | 0.357** | | |
| Interest expense to total deposits | 0.247** | −0.310** | 0.127 | −0.157* | 0.167* | −0.408** | −0.286** | 0.305** | −0.268** | 0.640** | 0.564** | 0.853** | 0.096 | −0.045 | 0.343** | 0.356** | 0.605** | |
| Mean | 0.329 | 1.987 | 0.027 | 15.085 | 0.074 | 0.154 | 0.011 | 249.53 | 0.523 | 2.190 | 0.162 | 0.028 | 3.760 | 0.597 | 0.399 | 0.836 | 0.260 | 0.040 |
| Standard deviation | 0.129 | 0.850 | 0.011 | 9.60 | 0.013 | 0.066 | 0.005 | 161.99 | 0.0075 | 1.981 | 0.119 | 0.0096 | 5.853 | 0.129 | 0.255 | 0.196 | 0.245 | 0.017 |

** Correlation is significant at the 0.01 level (two-tailed).
* Correlation is significant at the 0.05 level (two-tailed).

Table 3. Model selection heuristics for dynamic model with partitions

| Strategic groups | Dimensions | SSE | VAF | NP | LL | AIC | MAIC | BIC | CAIC | AdjR2 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1,658.594 | 0.136 | 18 | −2,593.659 | 5,223.318 | 5,241.318 | 5,281.953 | 5,299.953 | 0.073 |
| 2 | 1 | 1,264.256 | 0.342 | 21 | −2,396.490 | 4,834.980 | 4,855.980 | 4,903.387 | 4,924.387 | 0.277 |
| 3 | 1 | 1,190.757 | 0.380 | 24 | −2,359.740 | 4,767.481 | 4,791.481 | 4,845.661 | 4,869.661 | 0.303 |
| 4 | 1 | 1,160.906 | 0.395 | 27 | −2,344.815 | 4,743.630 | 4,770.630 | 4,831.582 | 4,858.582 | 0.304 |
| 5 | 1 | 1,136.004 | 0.408 | 30 | −2,332.364 | 4,724.728 | 4,754.728 | 4,822.453 | 4,852.453 | 0.302 |
| 2 | 2 | 1,215.348 | 0.367 | 35 | −2,372.036 | 4,814.072 | 4,849.072 | 4,928.085 | 4,963.085 | 0.244 |
| 3 | 2 | 1,052.219 | 0.452 | 41 | −2,290.472 | 4,662.943 | 4,703.943 | 4,796.501 | 4,837.501 | 0.316 |
| 4 | 2 | 969.256 | 0.495 | 47 | −2,248.990 | 4,591.980 | 4,638.980 | 4,745.083 | 4,792.083 | 0.340 |
| **5** | **2** | **896.739** | **0.533** | **53** | **−2,212.732** | **4,531.463** | **4,584.463** | **4,704.110** | **4,757.110** | **0.358** |
| 3 | 3 | 1,025.427 | 0.466 | 57 | −2,277.075 | 4,668.151 | 4,725.151 | 4,853.828 | 4,910.828 | 0.255 |
| 4 | 3 | 966.853 | 0.496 | 66 | −2,247.788 | 4,627.577 | 4,693.577 | 4,842.571 | 4,908.571 | 0.243 |
| 5 | 3 | 879.468 | 0.542 | 75 | −2,204.096 | 4,558.192 | 4,633.192 | 4,802.504 | 4,877.504 | 0.252 |
| 4 | 4 | 910.150 | 0.526 | 84 | −2,219.437 | 4,606.874 | 4,690.874 | 4,880.504 | 4,964.504 | 0.169 |
| 5 | 4 | 853.008 | 0.556 | 96 | −2,190.866 | 4,573.731 | 4,669.731 | 4,886.451 | 4,982.451 | 0.117 |
| 5 | 5 | 847.596 | 0.564 | 116 | −2,188.160 | 4,608.320 | 4,724.320 | 4,986.190 | 5,102.190 | −0.097 |

Key: SSE = sum squares error, VAF = variance accounted for, NP = number of independent parameters, LL = log-likelihood, AIC = Akaike information criterion, MAIC = modified Akaike information criterion, BIC = Bayesian information criterion, CAIC = consistent Akaike information criterion, AdjR2 = Adjusted R-square.

KEY: Figures 2–6

| Label | Variable Name |
|---|---|
| CR | Current ratio |
| DER | Debt-equity ratio |
| ISD | Total investment securities to total worldwide deposits |
| LIS | Gross loans to total investment securities |
| LA | Gross loans to total assets |
| LD | Gross loans to total worldwide deposits |
| BD | Total borrowings to total worldwide deposits |
| BA | Total borrowings to total assets |
| IA | Total interest expense to total assets |
| ID | Total interest expense to total worldwide deposits |

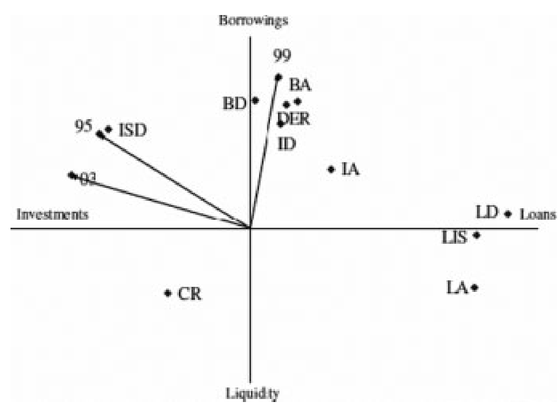


Figure 2. Estimated joint space: strategic group 1

Figure 2 also shows the evolution of the six banks in the first strategic group (*investments-borrowings* group), which seems to balance its focus between investments and borrowings in 1995, then move to a heavier focus on borrowings in 1999, and eventually return to the initial balanced focus in 2003 (see the Appendix for the composition of the derived strategic groups). The evolution of the 10 banks in the second strategic group, as we show in Figure 3, suggests naming these firms the *borrowings* group because they stay focused on borrowings over the entire nine-year period. Similar to the first strategic group, the banks in the third strategic group balance their focus on loans and liquidity in 1995, but they shift primarily to liquidity in 1999, and then return to the initial balanced focus in 2003 (see Figure 4 which depicts the *loans-liquidity* group). In Figure 5, we portray the evolution pattern of the fourth and largest strategic group, with its 24 banks, which we label the *liquidity* group. These banks evolve from a focus on loans in 1995 to a focus on liquidity in both 1999 and 2003. Finally, the *investments-liquidity* group, which consists of 14 banks, evolves from a focus on investments in 1995, to liquidity in 1999, and then to a balanced focus on investments and liquidity in 2003 (see Figure 6).

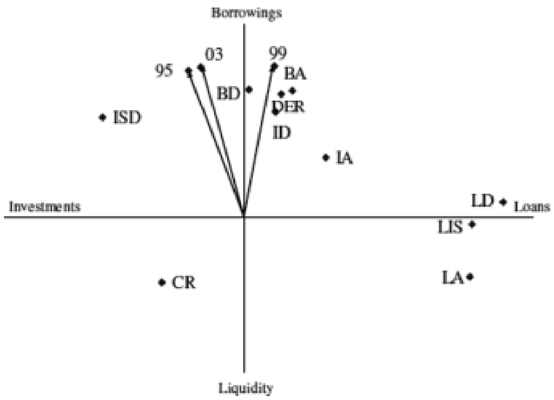


Figure 3. Estimated joint space: strategic group 2

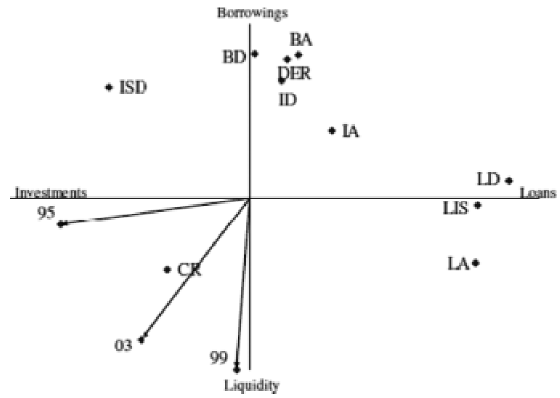


Figure 6. Estimated joint space: strategic group 5

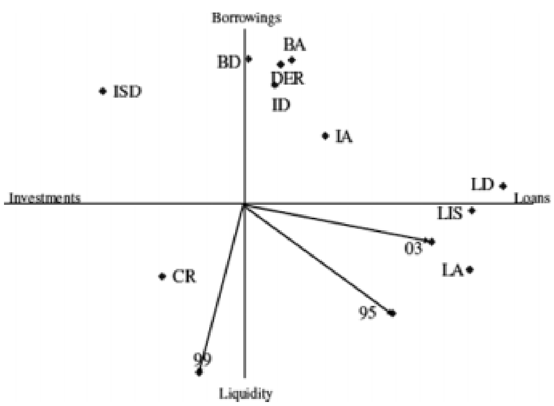


Figure 4. Estimated joint space: strategic group 3

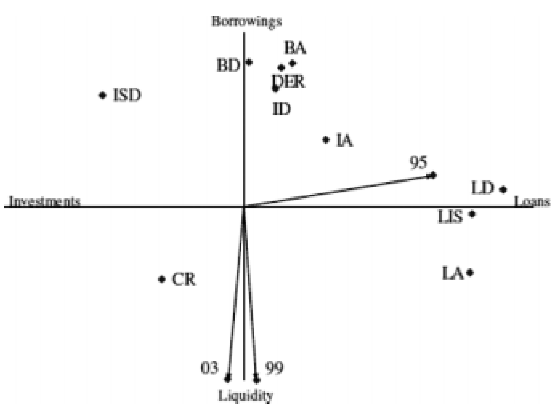


Figure 5. Estimated joint space: strategic group 4

## Validity of strategic groups

The critical question for strategic groups research relates to the validity of the identified strategic groups (Barney and Hoskisson, 1990; Dranove, Peteraf, and Shanley, 1998). Similar to extant research (e.g., Short *et al*., 2007), we assess *post hoc* whether any meaningful differences exist across the five strategic groups in terms of firm performance measures. We therefore use four measures to assess the *market value of the firm* (i.e., Tobin's q, market-to-book value, dividend yield, and price-to-earnings ratio), and four measures to assess *firm efficiency* (i.e., sales to total assets, net profit margin, return on assets, and sales per employee) (e.g., Brealey and Myers, 1988).

With data from 1995 to 2003 pertaining to these performance metrics, we resorted to a two-way analysis of variance for which the first factor is strategic group membership (three levels) and the second is year (nine levels). We use the nine years of data from 1995 to 2003 and present the results regarding the differences in the performance variables, as well as in the strategic variables, across the five strategic groups in Table 4. These *post hoc* contrasts are estimated by using Tukey's B test as implemented in SPSS. With two exceptions, the price-to-earnings ratio and sales per employee, the analysis of variance supports differences in firm performance across the five strategic groups ($p < 0.01$ for the main effect of the strategic groups factor). As Table 4 reveals, there are differences in the strategic variables as well among the five strategic groups.[4]

[4] We showed these five derived strategic groups to senior executives at a major bank in the Pittsburgh, Pennsylvania area (this bank competes in this tristate area) who confirmed the face validity of these strategic groups for the banks with which they were familiar in the sample.



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Table 4. *Post hoc* differences in firm performance and strategy variables across strategic groups

| Firm performance variable | Strategic group 1: investments-borrowings group | Strategic group 2: borrowings group | Strategic group 3: loans-liquidity group | Strategic group 4: liquidity group | Strategic group 5: investments-liquidity group |
|---|---|---|---|---|---|
| *Market value measures* | | | | | |
| Tobin's q | $0.285^{p}$ | $0.359^{qr}$ | $0.302^{p}$ | $0.327^{pq}$ | $0.391^{r}$ |
| Market-to-book value | $1.676^{p}$ | $2.282^{q}$ | $1.939^{p}$ | $1.889^{p}$ | $2.495^{q}$ |
| Dividend payout ratio | $0.025^{p}$ | $0.031^{q}$ | $0.030^{q}$ | $0.027^{pq}$ | $0.025^{p}$ |
| Price-to-earnings ratio | $15.736^{p}$ | $14.899^{p}$ | $16.432^{p}$ | $15.379^{p}$ | $16.496^{p}$ |
| *Firm efficiency measures* | | | | | |
| Sales to total assets | $0.072^{p}$ | $0.081^{q}$ | $0.079^{q}$ | $0.075^{p}$ | $0.082^{q}$ |
| Net income to total current operating revenue | $0.132^{p}$ | $0.158^{q}$ | $0.148^{pq}$ | $0.146^{pq}$ | $0.152^{pq}$ |
| Return on assets | $0.094^{p}$ | $0.127^{r}$ | $0.118^{qr}$ | $0.108^{pq}$ | $0.124^{qr}$ |
| Sales per employee | $239.090^{p}$ | $255.625^{p}$ | $237.553^{p}$ | $254.710^{p}$ | $266.826^{p}$ |
| *Firm strategy variables* | | | | | |
| Current ratio | $0.521^{p}$ | $0.522^{pq}$ | $0.524^{qr}$ | $0.525^{r}$ | $0.522^{pq}$ |
| Debt-to-equity ratio | $1.968^{pq}$ | $2.534^{q}$ | $1.630^{p}$ | $1.958^{pq}$ | $2.408^{q}$ |
| Total investment securities to total worldwide deposits | $0.413^{pq}$ | $0.334^{p}$ | $0.353^{pq}$ | $0.439^{q}$ | $0.337^{p}$ |
| Gross loans to total investment securities | $2.360^{p}$ | $7.399^{q}$ | $3.046^{p}$ | $3.259^{p}$ | $3.304^{p}$ |
| Gross loans to total asset | $0.617^{pq}$ | $0.607^{pq}$ | $0.634^{q}$ | $0.606^{pq}$ | $0.574^{p}$ |
| Gross loans to total worldwide deposits | $0.814^{p}$ | $0.902^{q}$ | $0.832^{p}$ | $0.840^{pq}$ | $0.830^{p}$ |
| Total borrowings to total worldwide deposits | $0.207^{pq}$ | $0.286^{q}$ | $0.193^{p}$ | $0.259^{pq}$ | $0.282^{pq}$ |
| Total borrowings to total asset | $0.147^{pq}$ | $0.179^{q}$ | $0.126^{p}$ | $0.157^{pq}$ | $0.179^{q}$ |
| Total interest expense to total asset | $0.035^{q}$ | $0.029^{p}$ | $0.031^{p}$ | $0.032^{pq}$ | $0.030^{p}$ |
| Total interest expense to total worldwide deposits | $0.046^{p}$ | $0.044^{p}$ | $0.042^{p}$ | $0.046^{p}$ | $0.044^{p}$ |

Notes: To compare the mean values across the strategic groups, we use Tukey's B *post hoc* contrast analysis, as implemented in SPSS, and assign the superscript $p$ to denote the lowest mean, then $r$ as the highest mean value ($p < 0.05$). In each row, the values with the superscript $p$ are the lowest and statistically equal. Similarly, in each row, the values with superscript $q$ are statistically equal and higher ($p < 0.05$) than those values with the superscript $p$. The mean values for return on assets are multiplied by 10 for ease of presentation.

## DISCUSSION

The concept of a strategic group recognizes that systematic similarities and differences exist among firms within an industry. This simple recognition of competitive heterogeneity has immense implications for strategic management issues, including identifying prevalent strategic recipes in an industry, mapping competitive dynamics, explaining interfirm performance differences, and, recently, providing insights into industry and firm dynamics (e.g., Dranove *et al*., 1998; Fiegenbaum and Thomas, 1990; Smith *et al*., 1997; Spender, 1989). Although emerging research on strategic group dynamics has provided rich theoretical developments, such as the cognitive basis for the existence of strategic groups (e.g., Reger and Huff, 1993) and strategic group identity theory (e.g., Peteraf and Shanley, 1997), it has been limited in terms of devising modeling techniques tailored to understanding these dynamics in strategic groups.

We began this research by recognizing the importance of studying strategic group dynamics and noting the inadequacies of current methods, such as the disjointed use of factor analysis and cluster analysis, to study such dynamics. Instead, we propose a new clusterwise bilinear multidimensional scaling (MDS) methodology for modeling the evolution of the derived strategic groups.



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The model selection heuristics devised are based on established information theory in statistics. We further illustrated this proposed methodology for public banks in the NY-OH-PA tristate region for 1995, 1999, and 2003. Two underlying dimensions and five strategic groups describe our data quite well, with very different evolutionary paths for the five derived strategic groups. We compared these results with those obtained by applying factor analysis and cluster analysis sequentially and thus demonstrated the much superior fit obtained by our proposed procedure. Statistical comparisons were also performed with several model variants including overlapping hybrid strategic groups and a static model. Our procedure can be gainfully used to derive strategic groups for any industry, any type of data, any specified time period, and any set of interval or ratio scale variables.

The proposed spatial clusterwise MDS technique also has implications for research in strategic management beyond strategic groups. As Ketchen and Shook (1996) observe, strategic management research focuses on four key domains of multidimensional constructs: strategy, environment, leadership/organization, and performance (also see Summers *et al*., 1990). One popular mechanism to study the interrelationships among these multidimensional constructs is to develop organizational configurations that provide a meaningful way to assess the complex reality that organizations face (e.g., Ketchen *et al*., 1997). For example, the popular organizational typology proposed by Miles and Snow (1978) describes all firms as belonging to one of four archetypes: defenders, prospectors, analyzers, or reactors. As aptly illustrated by DeSarbo *et al*. (2005), alternative strategic typologies can be methodologically derived that are optimal with respect to objective mathematical/statistical criteria. In a similar sense, the proposed spatial clusterwise MDS technique can be used to study the evolution of organizational configurations over time, based on multidimensional constructs.

Generally, the proposed spatial clusterwise MDS technique might also be adapted to study organizational dynamic capabilities, or a 'firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments' (Teece, Pisano, and Shuen, 1997: 516). Dynamic capabilities are systematic, persistent organizational features that offer managers control levers and intended effects that offer a means to achieve new resource configurations (e.g., Døving and Gooderham, 2008; Winter, 2000). Empirical studies of dynamic capabilities involve longitudinal data pertaining to the four key domains of multidimensional constructs that strategic management research relies on, with the objective of dynamically mapping the interplay between organizations and environment such that the organizations might shape the environment (e.g., Moliterno and Wiersema, 2007; Teece, 2007). As theoretical interest in such domains expands, we hope that quantitative methodologies such as the one proposed here will be appropriately adopted, adapted, and/or modified to investigate the research questions of interest.

Given the prominence of strategic groups in strategic management literature, we believe that developing modeling techniques that are suited for strategic groups remains a priority in need of immediate attention. Important questions persist regarding strategic group dynamics such as those related to changes over time in (1) group strategy, (2) group membership, and (3) number of strategic groups (Mascarenhas, 1989). Our proposed methodology adequately addresses only the first of these three issues. We purposely have restricted the number of strategic groups and their membership to be constant over time to explore the evolution and dynamics of their corresponding strategy and resulting performance. Obviously, the next methodological step would be to extend this procedure to model changes in strategic group membership and changes in the number of strategic groups explicitly. An approximation of this extension would be to apply the existing procedure separately to each time period's data. However, that approach would be somewhat overparameterized because of the huge number of additional parameters, the lack of identification of many model parameters, and the lack of parsimony in terms of separate $\underline{X}$, $\underline{Y}$, and $\underline{\delta}$.

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## APPENDIX: COMPOSITION OF THE FIVE DERIVED STRATEGIC GROUPS

### Strategic Group 1

| | |
|---|---|
| COMMUNITY BANK SYSTEM I | NY |
| FIRST FRANKLIN CORP | OH |
| CHESTER VY BANCORP INC | PA |
| COMMUNITY BANKS INC MLL | PA |
| HARLEYSVILLE NATL CORP/ | PA |
| HARLEYSVILLE SVGS FINL | PA |

### Strategic Group 2

| | |
|---|---|
| ALLIED IRISH BANKS -AD | NY |
| ARROW FINANCIAL CORP | NY |
| NORTH FORK BANCORPORATI | NY |
| STERLING BANCORP/NY | NY |
| WESTPAC BANKING CORP - | NY |
| KEYCORP | OH |
| BRYN MAWR BANK CORP | PA |
| FIDELITY BANCORP INC/PA | PA |
| FULTON FINANCIAL CORP | PA |
| PNC FINANCIAL SVCS GROU | PA |

### Strategic Group 3

| | |
|---|---|
| ELMIRA SVGS BANK FSB/NY | NY |
| SUFFOLK BANCORP | NY |
| TOMPKINSTRUSTCO INC | NY |
| TRUSTCO BANK CORP/NY | NY |
| FIRST FINL BANCORP INC/ | OH |
| AMERISERV FINANCIAL INC | PA |
| F N B CORP/FL | PA |
| ROYAL BANCSHARES/PA -C | PA |
| SUSQUEHANNA BANCSHARES | PA |
| REPUBLIC FIRST BANCORP | PA |

### Strategic Group 4

| | |
|---|---|
| ASTORIA FINANCIAL CORP | NY |
| N B T BANCORP INC | NY |
| NEW YORK CMNTY BANCORP | NY |

### (*Continued*) Strategic Group 4

| | |
|---|---|
| STATE BANCORP/NY | NY |
| U S B HOLDING INC | NY |
| BELMONT BANCORP | OH |
| CAMCO FINANCIAL CORP | OH |
| CORTLAND BANCORP | OH |
| FIRST DEFIANCE FINANCIA | OH |
| LNB BANCORP INC | OH |
| NATIONAL BANCSHARES COR | OH |
| OHIO VALLEY BANC CORP | OH |
| PARK NATIONAL CORP | OH |
| PVF CAPITAL CORP | OH |
| SKY FINANCIAL GROUP INC | OH |
| UNITED BANCORP INC/OH | OH |
| ESB FINANCIAL CORP | PA |
| LAUREL CAP GROUP INC | PA |
| LEESPORT FINANCIAL CORP | PA |
| PENNSYLVANIA COMM BANCO | PA |
| OMEGA FINANCIAL CORP | PA |
| S & T BANCORP INC | PA |
| STERLING FINANCIAL CORP | PA |
| WVS FINANCIAL CORP | PA |

### Strategic Group 5

| | |
|---|---|
| BANK OF NEW YORK CO INC | NY |
| FIRST LONG ISLAND CORP | NY |
| JPMORGAN CHASE & CO | NY |
| M & T BANK CORP | NY |
| FIFTH THIRD BANCORP | OH |
| FIRSTMERIT CORP | OH |
| HUNTINGTON BANCSHARES | OH |
| NATIONAL CITY CORP | OH |
| PEOPLES BANCORP INC/OH | OH |
| FIRST COMMONWLTH FINL C | PA |
| MELLON FINANCIAL CORP | PA |
| NATIONAL PENN BANCSHARE | PA |
| PARKVALE FINANCIAL CORP | PA |
| SOVEREIGN BANCORP INC | PA |