



The simultaneous identification of strategic/performance groups and underlying dimensions for assessing an industry's competitive structure

Wayne S. DeSarbo and Rajdeep Grewal

*Marketing Department, Smeal College of Business,
Pennsylvania State University, University Park, Pennsylvania, USA*

Heungsun Hwang

McGill University, Montreal, Canada, and

Qiong Wang

*Marketing Department, Smeal College of Business,
Pennsylvania State University, University Park, Pennsylvania, USA*

Abstract

Purpose – The purpose of this paper is to integrate aspects of the literature on strategic and performance groups and explicitly derive strategic/performance groups which exhibit differences with respect to both strategy and performance, as well as display associations and potential interrelationships between the two sets of variables.

Design/methodology/approach – A two-way clusterwise bilinear spatial model was formulated (e.g. a scalar products or vector multidimensional scaling model (MDS)) for the analysis of two-way strategic and performance data which simultaneously performs MDS and cluster analysis. An efficient alternating least-squares procedure was devised that estimates conditionally globally optimum estimates of the model parameters within each iterate in analytic, closed-form expressions.

Findings – This bilinear MDS methodology was deployed in the context of strategic/performance group estimation using archival data for public banks in the NY-NJ-PA tri-state area. For this illustration, four strategic/performance groups and two underlying dimensions were found.

Practical implications – Consideration of both strategy and performance data should be employed in describing the heterogeneity amongst firms competing in the same industry.

Originality/value – The paper provides a new spatial methodology to derive strategic/performance groups in any given industry to more completely summarize intra-industry heterogeneity.

Keywords Strategic groups, Organizational structures, Cluster analysis, Competitive strategy, Banking

Paper type Research paper



1. Introduction

Recognizing that considerable heterogeneity typically exists among firms in any industry (Fiegenbaum *et al.*, 1987; Hatten and Schendel, 1977; Scherer and Ross, 1990), scholars have proposed the notion of strategic groups where firms in the same strategic group own similar resources (Cool and Schendel, 1988), pursue similar strategies (Porter, 1979), and seemingly experience similar levels of performance

(Fiegenbaum and Thomas, 1990). Particularly, the strategic group literature recognizes that there are considerable differences in the strategies that firms within an industry follow (Caves and Porter, 1978; Hatten and Schendel, 1977; Hatten *et al.*, 1978), and focuses on uncovering such strategic recipes that are prevalent in an industry (Ketchen *et al.*, 1997; McGee and Thomas, 1986; Spender, 1989; Thomas and Venkatraman, 1988). For example, such aspects as cost structures, product diversification, formal organization, resources profiles, performance, and/or strategic variables are typically utilized to uncover the strategic recipes/postures within an industry (Cool and Schendel, 1987; Hatten and Hatten, 1987; Sudharshan *et al.*, 1991).

Although the initial research on strategic groups was empirically driven to find such discrete structures from data, recent research has been more theoretically driven where the emphasis has been on demarcating the existence and importance of strategic groups (Fiegenbaum and Thomas, 1995; Peteraf and Shanley, 1997; Tang and Thomas, 1992). For example, Peteraf and Shanley (1997) propose a theory of strategic group identity to explain how strategic groups emerge and influence firm behaviors and outcomes. Using social learning theory and social identification theory as the building blocks, Peteraf and Shanley (1997) suggest that managers cognitively partition the industry to reduce uncertainty and to cope with bounds on human rationality. Similarly, other scholars have also used managerial cognitions as the bases for justifying the viability and importance of strategic groups (Porac *et al.*, 1989; Reger and Huff, 1993).

With these theoretical developments, there is a growing recognition that researchers should pay attention to demonstrating that strategic groups exist by showing group persistence over time and by demonstrating that performance varies across the derived strategic groups (Dranove *et al.*, 1998; Wiggins and Ruefli, 1995). To this effect, meta-analytic evidence (Ketchen *et al.*, 1997) and recent empirical research (Ferguson *et al.*, 2000; Nair and Kotha, 2001; Short *et al.*, 2007) have typically shown relative stability in strategic groups over time. For example, using an expanded dataset, Osborne *et al.* (2001) found the same strategic groups in the pharmaceutical industry as did the prior study of Cool and Schendel (1987). Thus, contemporary research shows that strategic groups exist:

- in diverse industries such as retailing (Lewis and Thomas, 1990), banking (Amel and Rhoades, 1988), pharmaceuticals (Cool and Schendel, 1987), brewing (Tremblay, 1985), and insurance (Fiegenbaum and Thomas, 1990); and
- in varied countries such as Belgium (Houthoofd and Heene, 1997), India (Kumar, 1990), Japan (Nair and Filer, 2003), Spain (Amel and Rhoades, 1992), as well as in the USA (Cool and Schendel, 1987; Fiegenbaum and Thomas, 1990).

The consensus in these research streams seems to be that strategic groups do exist across many types of different industries, and that there is a high degree of convergence in the results across different data types (Ketchen *et al.*, 1997; Nath and Gruca, 1997; Porac and Thomas, 1994).

Historically, one of the key criticisms of strategic groups research emerges when researchers fail to find performance differences across strategic groups derived from using information only on firm strategic variables (Amel and Rhoades, 1988; Cool and Schendel, 1987; Frazier and Howell, 1983). Such equifinality (equal outcomes) has promoted scholars to raise questions such as “Do strategic really groups exist?”

(Barney and Hoskisson, 1990; Tang and Thomas, 1992). In fact, the litmus test for the existence of strategic groups has been to show in a *post hoc* manner significant differences in firm performance across strategic groups (Dranove *et al.*, 1998). To address this issue of performance differences head-on, Wiggins and Ruefli (1995) propose the notion of performance groups, which they define as “a set of firms whose performance levels are statistically indistinguishable from those of other firms in the group but are distinguishable from the performance levels of firms in other performance groups.” Therefore, Wiggins and Ruefli (1995) explicitly look for performance differences across firms and thus provide a creative solution for strategic group researchers who seek to identify meaningful heterogeneous groups such that there are differences in both strategic and performance variables across groups. Unfortunately, when deriving performance groups solely on the basis of an analysis of performance variables, there is no guarantee that the derived groups will necessarily display significant difference with respect to the strategies they employ (and vice versa). We build on this research on strategic and performance groups, and suggest that meaningful strategic/performance groups can be identified if one uses information on both strategic and performance variables to identify the groups, and employ suitable methodological procedures to derive them. In addition to this explicit motive of utilizing information on strategic and performance variables to identify strategic/performance groups, we propose a deterministic, non-parametric, clusterwise procedure that overcomes several weaknesses of traditional factor-cluster analyses methodologies used in strategic and performance groups research to identify strategic/performance groups. We now turn to motivating the development of this methodology.

The typical empirical methodology utilized to identify strategic or performance groups in any specified industry has traditionally involved some form of cluster analysis (such as *K*-means or hierarchical clustering analysis) on a set of firm level strategic and/or performance variables (Amel and Rhoades, 1988; Harrigan, 1985; Lewis and Thomas, 1990)[1]. Occasionally, researchers have first employed factor analysis to reduce the dimensionality of the variable battery, followed by cluster analysis on the reduced set of factor scores to identify strategic or performance groups (Baird *et al.*, 1987; Cool and Schendel, 1987; Fiegenbaum and Thomas, 1993)[2]. Strategic groups scholars (Barney and Hoskisson, 1990; Ketchen and Shook, 1996), along with a plethora of literature in the classification and psychometric arenas, aptly document the pitfalls of using cluster analysis alone or the sequential use of factor and cluster analysis (DeSarbo *et al.*, 1991a; Everitt, 1988; Vichi and Kiers, 2001; Wedel and Kamakura, 2000). As DeSarbo *et al.* (1991b), Ketchen and Shook (1996) and Wedel and Kamakura (2000) and others document, cluster analysis has several weaknesses that include: extreme reliance on the judgment of the researcher, a lack of any theoretical basis for selection of a particular clustering method, results contingent on the specific selection of clustering method, the lack of any meaningful objective function in many cluster analyses, *ad hoc* preprocessing of the input data affecting the results obtained, etc. In addition, using the naïve two-step approach of first conducting a factor analysis and then using cluster analysis to group the resulting factor scores has also been shown to be fraught with difficulties (Vichi and Kiers, 2001). Each procedure (factor analysis and cluster analysis) optimizes a very different loss function. In addition, different results are typically obtained depending upon which type of

factor analysis and/or cluster analysis is utilized (and there is no adequate economic/strategy theory to dictate what such methodological selections should be made a priori). Finally, as noted in the psychometric and classification literature (DeSarbo *et al.*, 1994 for citations), often times the minor factors extracted in step one are discarded for data reduction purposes, and these discarded factors often contain the most information about clusters or groupings in the data.

As an alternative, we develop a deterministic, non-parametric, clusterwise procedure for the analysis of two-way data which simultaneously conducts factor and cluster analyses to optimize a common objective function. Efforts to extend a clusterwise framework to multidimensional scaling (MDS) and classification have been limited to primarily parametric finite mixture or latent class MDS models (LCMDS) (DeSarbo *et al.*, 1994). In particular, LCMDS models for the analysis of preference/dominance data have been proposed by a number of different authors over the past 15 years employing either scalar products/vector (Slater, 1960; Tucker, 1960) or unfolding (Coombs, 1964) representations to two-way preference/dominance data. In such LCMDS models, vectors or ideal points of derived clusters are estimated in place of member individual firms. Thus, the number of parameters is significantly reduced relative to individual level MDS models. LCMDS models are traditionally estimated using the method of maximum likelihood (*E-M* algorithms are typically employed) for two-way data. Wedel and DeSarbo (1996) extend the entire family of exponential distributions to such LCMDS models for two-way preference/dominance data.

These finite mixture based LCMDS models have a number of limitations associated with them. One, they are parametric models which require the assumption of specific distributions. As such, violations of such distributional assumptions may invalidate the use of the procedure. Two, most of the LCMDS procedures are highly non-linear in nature and require very intensive computation. Such procedures typically utilize the *E-M* approach or gradient based estimation procedures which may take extensive computation time for a complete analysis (over dimensions and clusters) to be performed. Three, at best, only locally optimum solutions are typically reached and the analyses have to be repeated several times for each value of the dimensionality and number of groups. Four, the available heuristics employ various information criteria that typically result in different solutions being selected. For example, the Bayesian Information Criterion (BIC) and Consistent Akaike Information Criterion (CAIC) heuristics are considered as more conservative measures resulting in the selection of fewer dimensions and groups in contrast to Akaike Information Criterion (AIC) and Modified Akaike Information Criterion (MAIC) which are considered to be more liberal criterion. As discussed in Wedel and Kamakura (2000), there are still other heuristics utilized for model selection for such finite mixture models (e.g. ICOMP, NEC, etc.) which are equally plausible, but typically result in different solutions. Finally, these LCMDS procedures result in fuzzy posterior probabilities of membership which may be difficult to interpret or justify in applications requiring partitions (even though the underlying assumptions of latent class models involve partitions).

The deterministic, non-parametric, clusterwise procedure for the analysis of two-way data that we devise here to simultaneously identify strategic/performance groups and the dimensions underlying these strategic/performance groups primarily summarizes the structure amongst a set of strategic and performance variables all

measured on the same entity (firm). The goal is to simultaneously derive a single joint space where “strategic and performance groups” are represented by vectors and variables by coordinate points, and their interrelationship in the space denotes some aspect of the structure in the data. This approach does not require parametric assumptions, such as LCMDS procedures, and provides a concise spatial representation of the underlying structure of the input data, as to be illustrated shortly in the application to strategic/performance groups. The alternating least-squares estimation procedure developed is fast and efficient and converges in a matter of minutes on a PC (DeSarbo *et al.*, 2008a). Conditional globally optimum estimates of parameters are obtained within each iterate of the estimation.

2. The proposed clusterwise bilinear spatial MDS methodology

2.1 The model

A typical strategic/performance groups study contains data on firms in an industry (e.g. banks in our case) measured on a set of strategic and performance variables. The objective is to model this data to simultaneously identify strategic/performance groups and the underlying dimensions on which such groups are based. We use this scenario, which also applies to our dataset, to delineate the proposed model structure.

Let, $i = 1, \dots, N$ banks; $j = 1, \dots, J$ strategic and performance variables; $s = 1, \dots, S$ strategic/performance groups (unknown); $r = 1, \dots, R$ dimensions (unknown); Δ_{ij} = the value of performance or strategy variable j for bank i .

Then, we model the observed data as:

$$\Delta_{ij} = \sum_{s=1}^S P_{is} \sum_{r=1}^R X_{jr} Y_{sr} + b + \varepsilon_{ij}, \quad (1)$$

where X_{jr} , the r -th coordinate for variable j ; Y_{sr} , the r -th coordinate for strategic/performance group s (vector):

$$P_{is}, \begin{cases} 0 & \text{if bank } i \text{ is not classified in strategic/performance group } s, \\ 1 & \text{Otherwise;} \end{cases}$$

Such that:

$$P_{is} \in \{0, 1\},$$

$$\sum_s P_{is} = 1,$$

ε_{ij} , error (deterministic); b , an additive constant.

Visually, we posit a scalar products or vector MDS display of the structure in the data while simultaneously classifying banks into strategic/performance groups allowing for partitions or non-overlapping memberships. Like traditional vector MDS models (e.g. individual level MDS procedures like MDPREF by Carroll (1980) which here would estimate firm specific vectors, variable coordinates in a dimensional space), the orientation of the strategic/performance group vector points in the direction of higher strategy and/or performance, while the projection of a variable onto the

strategic/performance group vector indicates the level of that strategic/performance group on that particular variable. In Figure 1, we present a hypothetical solution with two underlying dimensions (the x -axis and y -axis; $R = 2$), three strategic/performance groups ($S = 3$) and ten strategic and performance variables ($J = 10$, labeled A-J) in order to describe the spatial relationships captured. In this illustration, banks classified in the first strategic/performance group (S_1) seem to perform well with respect to variables D, F, J. Banks classified to strategic/performance group two (S_2) perform well with respect to variables E and I. And, banks classified in strategic/performance group three (S_3) perform well with respect to variables A, C, and G. Sample heterogeneity with respect to the sample banks are represented *vis-à-vis* different vector orientations in the derived space. Thus, the objective of the proposed spatial methodology is to estimate simultaneously the strategic and performance variable coordinates (\underline{X}), the number of strategic/performance groups (S), the vector orientation per strategic/performance group (\underline{Y}), the number of dimensions (R), and the classification matrix (\underline{P}) given the input data ($\underline{\Delta}$).

2.2 Estimation procedure

Thus, given $\underline{\Delta}$ and values of S and R , our goal is to estimate $\underline{P} = ((P_{is}))$, $\underline{X} = ((X_{jr}))$, b , and $\underline{Y} = ((Y_{sr}))$ to minimize the following error sums of squares:

$$\text{Min } \underline{P}, \underline{X}, \underline{Y}, b \quad \Phi = \sum_{i=1}^I \sum_{j=1}^J \left[\Delta_{ij} - \sum_{s=1}^S P_{is} \sum_{r=1}^R X_{jr} Y_{sr} - b \right]^2 = \sum_i \sum_j \epsilon_{ij}^2, \quad (2)$$

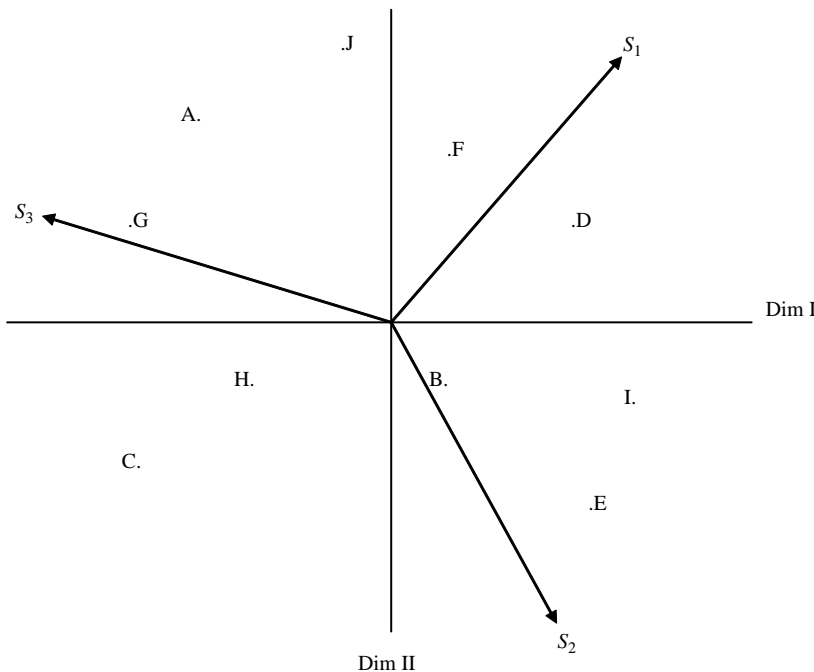


Figure 1.
Illustrative example:
 $S = 3$ strategic groups;
 $R = 2$ dimensions; $J = 10$
variables (A-J)

Let ${}_I\Delta_I = ((\Delta_{ij}))$, and define ${}_I P_S = ((P_{is}))$, ${}_S Y_R = ((Y_{sr}))$, and ${}_I X_R = ((X_{jr}))$. Then, one can rewrite model for this two-way data case as:

$$\Delta^* = P Y X' + \varepsilon, \quad (3)$$

where $\Delta^* = \Delta - b$. We now wish to estimate b , P , Y , and X , given Δ and a value of S and R , so as to:

$$\begin{aligned} \text{Min } \Phi &= \text{Min } tr(\underline{e}' \underline{e}) \\ &= tr[(\Delta^* - P Y X')'(\Delta^* - P Y X')] \end{aligned} \quad (4)$$

$$= tr[\Delta^* \Delta^{*'} - \Delta^* P Y X' - X Y P' \Delta^{*'} + X Y' P' P Y X'] \quad (5)$$

$$= tr(\Delta^* \Delta^{*'}) - 2tr(\Delta^* P Y X') + tr(X Y' P' P Y X'). \quad (6)$$

We now outline the alternating least-squares algorithm devised for this two-way model estimation modifying the three-way approach given in DeSarbo *et al.* (2008a, b).

2.2.1 Estimate X. Starting with the first order conditions, we calculate the partial derivatives of the error sums-of-squares expression (2) with respect to \underline{X} :

$$\frac{\partial \Phi}{\partial \underline{X}} = \frac{\partial}{\partial \underline{X}} [-2tr(\underline{A} \underline{X}') + tr(\underline{X} \underline{B} \underline{X}')], \quad (7)$$

where:

$$\underline{A} = \Delta^{*'} P Y, \quad (8)$$

$$\underline{B} = Y' P' P Y; \quad (9)$$

thus:

$$\frac{\partial \Phi}{\partial \underline{X}} = -2\underline{A} + \underline{X}(\underline{B} + \underline{B}'), \quad (10)$$

given the properties of the trace operation and its partial derivatives. Since \underline{B} is symmetric, $\underline{B} = \underline{B}'$, and the first order conditions give:

$$-2\underline{A} + 2\underline{X} \underline{B} = \underline{0}. \quad (11)$$

Solving for \underline{X} :

$$\begin{aligned} \hat{\underline{X}} &= \underline{A} \underline{B}^{-1} \\ &= \Delta^{*'} P Y (Y' P' P Y)^{-1}, \end{aligned} \quad (12)$$

which is estimable only for $R < S$ (an identification restriction).

2.2.2 Estimate Y. Starting with the first order conditions, we calculate the partial derivatives of the error sums-of-squares expression (2) with respect to \underline{Y} :

$$\frac{\partial \Phi}{\partial \underline{Y}} = \frac{\partial}{\partial \underline{Y}} \text{tr}[-2\Delta^* \underline{P} \underline{Y} \underline{X}' + \underline{X} \underline{Y}' \underline{P}' \underline{P} \underline{Y} \underline{X}'] \quad (13)$$

$$= \frac{\partial}{\partial \underline{Y}} \left[\text{tr}(-2\Delta^* \underline{P} \underline{Y} \underline{X}') + \text{tr}(\underline{X} \underline{Y}' \underline{P}' \underline{P} \underline{Y} \underline{X}') \right] \quad (14)$$

$$= \frac{\partial}{\partial \underline{Y}} [-2\text{tr}(\underline{C} \underline{Y} \underline{X}') + \text{tr}(\underline{X} \underline{Y}' \underline{Q} \underline{Y} \underline{X}')] \quad (15)$$

where:

$$\underline{C} = \underline{\Delta}' \underline{P}. \quad (16)$$

$$\underline{Q} = \underline{P}' \underline{P}. \quad (17)$$

Then:

$$-2\underline{X}' \underline{\Delta}^* \underline{P} + \underline{P}' \underline{P} \underline{Y} \underline{X}' \underline{X} + (\underline{P}' \underline{P})' \underline{Y} (\underline{X}' \underline{X})' = \underline{\Delta}, \quad (18)$$

and:

$$\hat{\underline{Y}}' = (\underline{X}' \underline{X})^{-1} \underline{X}' \underline{\Delta}^* \underline{P} (\underline{P}' \underline{P})^{-1}. \quad (19)$$

2.2.3 Estimate P. Note, $P_{is} = \{0, 1\}$ and represents the membership indicator binary variables such that:

$$\sum_s P_{is} = 1, \quad \forall_i, \text{ and} \quad (20)$$

$$\sum_i P_{is} > R, \quad \forall_s. \quad (21)$$

Then, one can rewrite Φ as:

$$\Phi = \text{tr}(\underline{\varepsilon} \underline{\varepsilon}') \quad (22)$$

$$= \text{tr}(\underline{\varepsilon} \underline{\varepsilon}') \quad (23)$$

$$= \sum_{i=1}^I H_{ii}, \quad (24)$$

where $\underline{H} = \underline{\varepsilon} \underline{\varepsilon}'$; so:

$$= \sum_{i=1}^I (\underline{\Delta}_i^* - \underline{P}_i \underline{Y} \underline{X}')' (\underline{\Delta}_i^* - \underline{P}_i \underline{Y} \underline{X}'). \quad (25)$$

Since $\underline{\Delta}_i^*$ and \underline{P}_i only affect Φ in i -th observation, the optimization here is separable over i . That is, can conditionally minimize equation (25) by observation to obtain a conditionally global optimum \underline{P} given \underline{X} , \underline{Y} , and $\underline{\Delta}^*$. For each i , we minimize $\Phi_i = \underline{\varepsilon}_i^* \underline{\varepsilon}_i'$ with respect to \underline{P}_i . Here, we enumerate over all S solution options for each \underline{P}_i (ignoring 0) to minimize $\Phi_i \forall i$.

2.2.4 Estimate b. We first define:

$$\hat{\Delta}_{ij} = \sum_{s=1}^S \hat{P}_{is} \sum_{r=1}^R \hat{X}_{jr} \hat{Y}_{sr}, \quad (26)$$

where, $\underline{L} = \text{vec}(\underline{\Delta}_{ij})$; $\underline{K} = (\underline{1}, \underline{M})$; $\underline{1}' = (1, 1, \dots, 1)$; $\underline{M} = \text{vec}(\hat{\Delta}_{ij})$.

Then, we can formulate this estimation problem as a simple least-squares one, and calculate:

$$\begin{pmatrix} \hat{b} \\ \hat{a} \end{pmatrix} = (\underline{K}' \underline{K})^{-1} \underline{K}' \underline{L}. \quad (27)$$

Note, the multiplicative constant (a) is not identifiable since it can be (and is) directly embedded into \underline{X} or \underline{Y} and set equal to 1.00.

2.2.5 Test for convergence. We can calculate an overall variance accounted for statistic (DeSarbo and Carroll, 1985) akin to an R^2 as:

$$\text{VAF} = 1 - \frac{\sum_{i=1}^N \sum_{j=1}^J (\Delta_{ij} - \hat{\Delta}_{ij})^2}{\sum_{i=1}^N \sum_{j=1}^J (\Delta_{ij} - \bar{\Delta}_{ij})^2}, \quad (28)$$

where:

$$\bar{\Delta}_{..} = \frac{1}{NJ} \sum_{i=1}^N \sum_{j=1}^J \Delta_{ij}. \quad (29)$$

If $\text{VAF}^{(IT)} - \text{VAF}^{(IT-1)} \leq 0.0001$, output all parameters estimated and stop; otherwise increase $IT = IT + 1$ and return to Step 1.

Note, each step A-D of this alternating least-squares algorithm provides a global optimum solution conditioned on holding fixed all the other parameter sets. In addition, steps A, B, and D are analytical closed form expressions which do not require much computational time. However, these desirable properties by no means guarantee a global optimum solution after convergence. Like its LCMDS counterparts, the proposed methodology is also subject to locally optimum solutions, and thus the procedure needs to be executed numerous times from different random starting points to check for globally optimum solutions as in the case of LCMDS.

3. Application: strategic/performance groups in banking

3.1 Background

Banking represents an important economic sector and thus has been the research context for a host of strategic group studies (Amel and Rhoades, 1988; McNamara *et al.*, 2003; Mehra, 1996; Ruiz, 1999; Serrano-Cinca, 1998; Zuniga-Vicente *et al.*, 2004; DeSarbo and Grewal, 2008; DeSarbo *et al.*, 2008c). As the banking sector represents a turbulent environment with fuzzy boundaries, identifying strategic groups in the banking industry is considered to be a non-trivial and an important problem (Amel and Rhoades, 1992; Fiegenbaum and Thomas, 1993). For studying strategic/performance groups in banks, it makes sense to use archival data due to governmental regulations, the fact that a host of secondary data is readily available, and that such data go well beyond the mere financial strategy of the bank (as signaled by liquidity and leverage ratios, as well as encompassing the two primary product portfolios of banks – loans and deposits) (Amel and Rhoades, 1988; McNamara *et al.*, 2003; Mehra, 1996; Slater and Zwirlein, 1996; DeSarbo and Grewal, 2008). Thus, we collected archival data from the COMPUSTAT database.

3.2 Variable operationalization

As competition in banking is largely driven by geographic constraints (i.e. customers are unwilling to travel for long distances for their banking needs), strategic groups research in banking tends to focus on geographically restricted areas (McNamara *et al.*, 2003; Serrano-Cinca, 1998; Zuniga-Vicente *et al.*, 2004; DeSarbo and Grewal, 2008). We have also verified this geographically restrictive notion of competition in discussions with several bank executives. As a result, we utilize archival data from the COMPUSTAT Banks Database for the year 2004 for the Tri-State area of NJ-NY-PA which contains complete records for some 111 public banks[3].

In terms of input variable batteries used for identifying strategic/performance groups, we first conducted a vast literature search of the banking, finance, and strategy literatures. Appendix provides a thorough taxonomy of the various performance and strategic measures encountered in this search. Unfortunately, not all of the various financial ratios listed in the Appendix are computable in COMPUSTAT given difficulties with missing data and the unavailability of some of the components of many of these ratios. As such, we follow DeSarbo and Grewal (2008) in using:

- market value ratios;
- profitability and efficiency ratios;
- liquidity and leverage ratios;
- product portfolio of loans; and
- product portfolio of deposits which comprise a major portion of the variable types listed in the Appendix.

We present the definition and formulae for each measure used in our analysis in Table I. We use Tobin's q , market-to-book value, dividend yield, and price-to-earnings ratio to assess market value (Brealey and Myers, 1988). These performance ratios signal the intangible value of the firm and capture future earning potential in addition to current earnings (Tobin, 1969; Wernerfelt and Montgomery, 1988). We use the approximation detailed in Chung and Pruitt (1994) to operationalize Tobin's q (Table I)

Table I.
Bank performance and
strategy variables

Variable category	Variable name (label)	Formulae
Market value ratios	Tobin's q (TQ)	$Q = (MVE + PS + DEBT) / TA$, where $Q =$ Tobin's q , MVE = (closing price of share at the end of the financial year)*(number of common shares outstanding), PS = liquidating value of the firm's outstanding preferred stock, DEBT = (current liabilities – current assets) + (book value of inventories) + (long-term debt), and TA = Book value of total assets Stock price/(total book value/number of shares outstanding)
Efficiency ratios	Market-to-book ratio (MBR)	Dividend per share/stock price
	Dividend yield (DY)	Stock price/earning per share
	Price-earnings ratio (PER)	T total current operating revenue/total assets
	Sales to total assets (STA)	Net income/total current operating revenue
	Net profit margin (NPM)	Net income/total assets
	Return on assets (RTA)	T total current operating revenue/number of employees
	Sales per employee (SPE)	Gross total assets/(total liability excluding valuation of reserves + total liability reserves and capital accounts)
Liquidity and leverage ratios	Current ratio (CR)	T total borrowing/book value
	Debt-equity ratio (DER)	T total borrowing/total assets
	Total borrowing to total assets (BA)	T total interest expense/total assets
	Interest expense to total assets (IA)	Gross loans/total investment securities
Product ratios – loans	Gross loans to total securities (LIS)	Gross loans/total assets
	Gross loans to total assets (L/A)	T total investment securities/total worldwide deposits
Product ratios – deposits	Total investment securities to total deposits (ISD)	Gross loans/total worldwide deposits
	Gross loans to total deposits (LD)	T total borrowings/total worldwide deposits
	Total borrowings to total deposits (BD)	Interest expense/total worldwide deposits
	Interest expense to total deposits (ID)	

which is often used in empirical research (Bharadwaj *et al.*, 1999; Lee and Grewal, 2004). To assess bank efficiency and profitability performance, we use:

- sales to total assets;
- net profit margin;
- return on assets; and
- sales per employee (Brealey and Myers, 1988).

The strategic variables utilized capture liquidity, leverage, loans, and deposits. We use the current ratio, which is defined as the ratio of current assets to current liabilities, to capture firm liquidity, and:

- debt-to-equity ratio;
- total borrowing to total assets; and
- interest expense to total assets as indicators of leverage ratio (Brealey and Myers, 1988).

For the product portfolio of loans, we use the ratios of gross loans to total investment securities and gross loans to total assets (Rose, 1999; Ruiz, 1999). For the product portfolio of deposits, we use 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.

Note, data on bank competitive activities regarding specific services (e.g. money market deposits, checking accounts, stock/bond transactions, various interest rates, loan/mortgage applications and accounts, promotions and advertising, etc.) were not available in COMPUSTAT. We present the descriptive statistics for these various strategic and performance related variables (in non-standardized form) in Table II.

Note, even though the constructs that are used to derive strategic groups vary across industrial contexts (McGee and Thomas, 1986), some scholars have focused on both performance and strategic variables (Frazier and Howell, 1983; Lewis and Thomas, 1990) to define strategic groups (not merely upon just strategic variables alone). The inclusion of both strategy and performance variables in an analysis makes it possible to account for unobserved heterogeneity (DeSarbo *et al.*, 2007, 2008c). For example, consider the case of two firms that have same values on strategic variables, but different values on performance variables. A possible reason for such a possibility could be that unobserved firm heterogeneity that has not been totally accounted for by strategic variables alone. The additional benefits of including strategy and performance variables to identify groups include:

- by including performance measures such as Tobin's q one is able to capture organizational intangible value (Wernerfelt and Montgomery, 1988);
- the stock market valuation of the firm can also be obtained from taking Tobin's q in tandem with ROA – that is, stock price reflects current profitability and/or future potential;

Variable category	Variable name	Mean	SD
Market value ratios (performance)	Tobin's q	0.3585	0.1122
	Market-to-book ratio	2.1517	0.7514
	Dividend yield	0.0223	0.0121
	Price-earnings ratio	20.6214	20.0369
Efficiency and profitability ratios (performance)	Sales to total assets	0.05618	0.0109
	Net profit margin	0.1791	0.0724
	Return on assets	0.0100	0.0044
	Sales per employee	245.3800	135.6539
Liquidity and leverage ratios (strategic)	Current ratio	0.5249	0.0086
	Debt-equity ratio	2.0240	1.6104
	Total borrowing to total assets	0.1675	0.1063
	Interest expense to total assets	0.0155	0.0056
Product ratios – loans (strategic)	Gross loans to total securities	2.5375	2.1636
	Gross loans to total assets	0.5823	0.1301
Product ratios – deposits (strategic)	Total investment securities to total deposits	0.4504	0.2749
	Gross loans to total deposits	0.8135	0.1866
	Total borrowings to total deposits	0.2629	0.2308
	Interest expense to total deposits	0.0226	0.0110

Table II.
Sample descriptive statistics

- there is historical precedent where some strategic groups researchers have included performance measures while deriving strategic groups (Harrigan, 1985; Ruiz, 1999);
- if one is interested in finding performance differences across strategic groups, then one approach would be to explicitly model these differences, where this approach is consistent with Wiggins and Ruefli (1995) who examine the possibility of the existence of performance groups (using Tobin's q and ROA) to suggest that if there are no performance differences across firms in an industry then strategic groups do not exist; and
- the approach we undertake provides a concise spatial summary of the interrelationships between the input variables and will spatially depict the associations between strategic and performance variables.

In any event, our proposed clusterwise methodology is sufficiently flexible to accommodate any specification of the input variables in any application setting (industry).

Finally, do note that the proposed clusterwise MDS procedure that we are devising is able to identify instances when the strategy and performance variables have differential effects – i.e. in such cases, strategy and performance variables would load on different dimensions. As a result, the inclusion of performance variables for strategic/performance group identification does not lessen our ability to identify underlying strategic recipes nor does it in any way compromise our ability to ascertain the validity of the identified groups. In summary, to identify strategic/performance groups in banking for our illustration, we include items from five different variable batteries:

- (1) market value ratios;
- (2) efficiency ratios;
- (3) liquidity and leverage ratios;
- (4) product portfolio of loans; and
- (5) product portfolio of deposits.

Note, prior to all analyses, we standardized each variable to zero mean and constant variance given their different scales of measurement.

4. The empirical results

We performed analyses for $R < S = 1, \dots, 5$ for the proposed methodology. For each run, we performed ten analyses and selected the best fitting solution for values of S and R . Based on the values of these goodness-of-fit values and subsequent interpretation, we select the $R = 2$ dimensions and $S = 4$ strategic and performance groups solution as the most parsimonious solution with a corresponding VAF of 0.347 with estimating a total of only 45 model parameters plus the classifications[4].

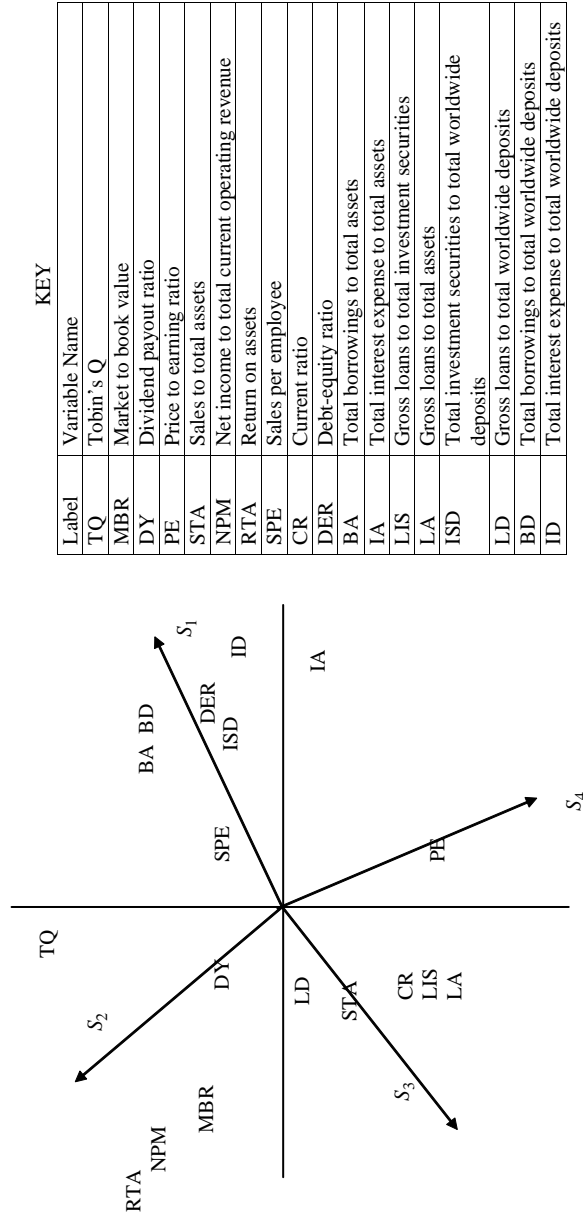
In Figure 2, we present the resulting joint space for the 2D model ($R = 2$) with four strategic and performance groups ($S = 4$). The size of the four derived strategic/performance groups are 19, 26, 32, and 34 firms, respectively. The first of the two dimensions (i.e. the horizontal x -axis) differentiates banks based on product ratios of loans and deposits, where larger values on the x -axis indicate lower emphasis on loans and deposits. Thus, traditional banks that lay emphasis on loans and deposits seem to belong to strategic/performance Groups 2 and 3, and non-traditional banks seem to populate strategic/performance Group 1. We can interpret the second dimension (the vertical y -axis) as intangible value with high positive values on the y -axis signaling high intangible value. Thus, strategic/performance Group 3 consists of traditional banks (low on x -axis) with highest levels of intangible value (highest on y -axis).

In Table III, we present the descriptive statistics for the four-strategic/performance group solution. From Figure 2 and this table, it is evident that the four strategic/performance groups are indeed quite different. Banks in the first strategic/performance group seem to be high on leverage ratios, but low with respect to the ratios of the product portfolios of loans and deposits. For leverage ratio, the banks in this strategic/performance group are more leveraged as shown by high values of:

- debt to equity ratio;
- borrowings to assets ratio; and
- interest expense to assets.

These banks also have lowest relative amount of loans as shown by loans to securities ratios and loans to assets ratios. Similar to loans, the emphasis on deposits is also low as shown by high values of:

- investment securities to deposits ratio;
- borrowings top deposit ratio; and
- interest expense to deposits ratio.



KEY

Label	Variable Name
TQ	Tobin's Q
MBR	Market to book value
DY	Dividend payout ratio
PE	Price to earning ratio
STA	Sales to total assets
NPM	Net income to total current operating revenue
RTA	Return on assets
SPE	Sales per employee
CR	Current ratio
DER	Debt-equity ratio
BA	Total borrowings to total assets
IA	Total interest expense to total assets
LIS	Gross loans to total investment securities
LA	Gross loans to total assets
ISD	Total investment securities to total worldwide deposits
LD	Gross loans to total worldwide deposits
BD	Total borrowings to total worldwide deposits
ID	Total interest expense to total worldwide deposits

Figure 2.
The derived $S = 4, R = 2$
joint space

Variable category	Variable name	Strategic/performance groups			
		S ₁ (n = 19)	S ₂ (n = 26)	S ₃ (n = 32)	S ₄ (n = 34)
Market value ratios (performance)	Tobin's <i>q</i>	0.4483 ^q	0.3144 ^b	0.4033 ^q	0.2969 ^b
	Market-to-book ratio	1.9239 ^b	2.2167 ^q	2.5814 ^q	1.8020 ^b
	Dividend yield	0.0206 ^q	0.0208 ^q	0.0282 ^q	0.0186 ^b
Efficiency and profitability ratios (performance)	Price-earnings ratio	17.7488 ^b	19.0580 ^b	17.0162 ^b	27.1124 ^b
	Sales to total assets	0.0492 ^b	0.0590 ^q	0.0597 ^q	0.0545 ^q
	Net profit margin	0.1374 ^b	0.2061 ^q	0.2322 ^q	0.1286 ^b
	Return on assets	0.0065 ^b	0.0121 ^q	0.0135 ^q	0.0069 ^b
Liquidity and leverage ratios(strategic)	Sales per employee	355.7753 ^q	189.8936 ^b	246.2866 ^b	224.6290 ^b
	Current ratio	0.5191 ^b	0.5290 ^q	0.5247 ^q	0.5251 ^q
	Debt-equity ratio	4.5602 ^q	0.8525 ^b	1.9109 ^q	1.5998 ^q
Product ratios – loans (strategic)	Total borrowing to total assets	0.3159 ^q	0.0872 ^b	0.1740 ^q	0.1389 ^q
	Interest expense to total assets	0.0216 ^q	0.0127 ^b	0.0135 ^q	0.0163 ^q
	Gross loans to total securities	1.2180 ^b	4.3345 ^q	1.7617 ^q	2.6572 ^q
	Gross loans to total assets	0.4570 ^b	0.6771 ^q	0.5359 ^q	0.6262 ^q
	Total investment securities to total deposits	0.8081 ^q	0.2651 ^b	0.4828 ^q	0.3582 ^b
Product ratios – deposits (strategic)	Gross loans to total deposits	0.7808 ^b	0.8601 ^b	0.7656 ^b	0.8434 ^b
	Total borrowings to total deposits	0.5862 ^q	0.1152 ^b	0.2583 ^q	0.1977 ^q
	Interest expense to total deposits	0.0382 ^q	0.0161 ^b	0.0195 ^b	0.0218 ^q

Notes: We use the superscript *b* to denote the lowest value, *q* for the next highest, and *r* for the highest. For example, for interest to total expense the lowest value is for strategic/performance Group 2 (0.0161) that statistically equals the value for strategic/performance Group 3 (0.0195), which in turn equals the value for strategic/performance Group 4 (0.0218), and strategic/performance Group 1 has the highest value (0.0382). Finally, banks in the four strategic/performance groups are similar in terms of size as indicated by total assets and number of employees. The differences in mean across strategic/performance groups are computed using Tukey's *B* test as implemented in SPSS

Table III.
Strategic/performance
group specific descriptive
statistics

Thus, it seems that the first strategic/performance group consists of non-traditional banks such as J.P. Morgan Chase, Fidelity Bancorp, and New York Community Bancorp. These banks are highly valued in terms of Tobin's q (the highest, but statistically equivalent to strategic/performance Group 3), but have lowest levels of current performance as shown by efficiency ratios of sales to assets, net profit margin, and return on assets. Thus, the emphasis on banks in the first strategic/performance group seems to be in creating intangible value as opposed to short-term performance. The heterogeneity amongst the four strategic/performance groups can be easily witnessed by the vast dispersion in vector orientations clearly shown in Figure 2.

Banks in the second strategic/performance group seem to lay emphasis on the product ratios of loans and deposits, and are less leveraged than banks in strategic/performance Group 1. For loans, the banks in this strategic/performance group have the highest ratio of loans to securities and loans to assets (higher than strategic/performance Groups 1 and 3, but statistically equal to strategic/performance Group 4). Similarly for deposit ratios, where the banks are low on:

- investment securities to deposit ratios (statistically equal to strategic/performance Group 4);
- borrowing to deposit ratio (statistically equal to strategic/performance Group 4); and
- interest expense to deposits (statistically equal to strategic/performance Group 3).

Thus, traditional banks such as M&T Bank and Bryn Mawr Bank that inhabit strategic/performance Group 2 are statistically equal to strategic/performance Groups 3 and 4 in terms of market value ratios and efficiency ratios.

Strategic/performance Group 3 consists of top performing banks in terms of market value ratios and efficiency ratios. For market value ratios, banks in this strategic and performance group are highest on three ratios, i.e.:

- (1) Tobin's q (statistically equal to strategic/performance Group 1);
- (2) market to book value (statistically equal to strategic/performance Group 2); and
- (3) dividend yield (statistically equal to strategic/performance Group 2).

Similarly, the banks have highest value on three efficiency ratios, i.e.:

- (1) sales to assets (statistically equal to strategic/performance Groups 2 and 4);
- (2) net profit margin (statistically equal to strategic/performance Group 2); and
- (3) return on assets (statistically equal to strategic/performance Group 2).

For leverage ratios and products ratios relating to loans and deposits, the banks in this strategic/performance group fall somewhere in the middle. Thus, banks such as Bank of New York and PNC financial services seem to be blending strategies of strategic/performance Groups 1 and 2.

Poor performing banks on both market value ratios and efficiency ratios characterize strategic/performance Group 4. With leverage and liquidity ratios similar to strategic/performance Groups 2 and 3 (i.e. more in line with traditional banking), these banks are on the high end for loans, but somewhere in the middle for deposits. For example, strategic/performance Group 4 banks, such as Lakeland Bank Corp and

Flushing Financial Corp, have the highest ratio of loans to assets (statistically equal to strategic/performance Group 2). In sum, non-traditional banks seem to be in strategic/performance Group 1, traditional banks that lay emphasis on loans and deposit seem to belong to strategic/performance Group 2, traditional high performing banks inhabit strategic/performance Group 3, and traditional low performing banks populate strategic/performance Group 4.

Finally, to assess the external validity of the results, we compared the strategic and performance group membership with key competitors as reported in Yahoo Finance web site (<http://finance.yahoo.com/>, accessed 9 January 2008). One would expect that the banks in the same strategic/performance groups compete with one another. With some exceptions (e.g. none of the competitors of M&T Bank were in our dataset and occasional competing banks as per Yahoo Finance belonged to different strategic/performance groups), we did find that the 2-3 competitors identified in Yahoo Finance were in the same strategic/performance group. For example, according to the Yahoo Finance web site Mellon Bank has three primary competitors: Bank of New York, Citigroup, and State Street CP. Of the three, only Bank of New York was in our dataset and it belonged to strategic/performance Group 3, the same strategic/performance group as Mellon Bank. Similarly, New York Community Bancorp had two competitors identified in Yahoo Finance: Astoria Financial Corp and JP Morgan Chase Co. These three banks belonged to the first strategic/performance group. Thus, evidence can be found to support external validity for our analysis and results.

5. Discussion

Research in strategy recognizes that considerable differences typically exist amongst firms in an industry and models these differences by identifying strategic or performance groups in an industry (Cool and Schendel, 1988; Ketchen *et al.*, 1997; McGee and Thomas, 1986). From an empirical standpoint, some combination of factor analysis and/or cluster analysis has been traditionally utilized to identify such groups in an industry and the underlying dimensions on which the derived groups are based. The vast literature in the classification and psychometrics arena (DeSarbo *et al.*, 1991a; Vichi and Kiers, 2001) documents the weaknesses associated with the sequential application of these method, which we summarized earlier. To overcome these weaknesses, we devised a clusterwise bilinear spatial model (e.g. scalar products or vector multidimensional scaling models) for the analysis of two-way strategic and performance data. We utilize an efficient alternating least-squares procedure that estimates conditionally globally optimum estimates of the model parameters within each iterate with analytic closed-form expressions. We deploy the bilinear multidimensional scaling methodology in the context of banking using archival data for public banks in the NY-NJ-PA tri-state.

For our data on banks, we find that a two-dimensional solution with four strategic/performance groups seems to most parsimoniously represent the underlying structure in the data. The two dimensions seem to differentiating banks on the product ratios of loans and deposits (x -axis of Figure 2) and intangible value (y -axis). For the strategic/performance groups, we find that non-traditional banks seem to belong to strategic/performance Group 1, traditional banks that lay emphasis on heavy loans and deposit are in strategic/performance Group 2, traditional high performing banks

dwelling in strategic/performance Group 3, and traditional low performing banks occupy strategic/performance Group 4. The ability of the proposed method to simultaneously identify dimensions and strategic/performance group membership is indeed insightful.

For the purpose of simultaneously identifying strategic/performance groups and the underlying dimensions on which the strategic/performance groups are based, we have introduced a clusterwise bilinear spatial MDS model that performs data reduction and classification simultaneously. Unlike its latent class LCMDS counterparts, the procedure is non-parametric and does not require distributional assumptions for estimation purposes. In addition, the alternating least squares estimation algorithm for parameter estimation renders conditionally globally optimum estimates at each stage of the estimation per iterate in a relatively quick manner, as opposed to more computationally intensive LCMDS methods which may require hours for convergence for designated R and S combination runs. We have discussed the many difficulties associated with the traditional two-step approach of first dimension reduction followed by cluster analysis. In addition, we have empirically demonstrated the superiority of the proposed approach over traditional two-step approaches in terms of explaining the structure of the input data (i.e. VAF). The procedure can accommodate internal or external analyses (i.e. it can be utilized where X , Y , and/or P is fixed in the analysis) in order to test specified model structures. The proposed spatial methodology can be employed for deriving strategic groups, performance groups, and/or strategic/performance groups depending upon the user's input variable selection. It is currently appropriate for metric analysis accommodating either ratio or interval measurement scales.

Although we make importance advances to the identification of strategic/performance groups and the underlying dimensions on which the strategic/performance groups are based, future research can extend our research in a number of directions. First, a fully non-metric version would be useful for applications involving ordinal scales of measurement. Second, extending the utility model specification to an ideal point or unfolding model would prove advantageous. Third, more extensive testing of the procedure would be desirable via thorough Monte Carlo testing with synthetic data structures. Finally, research on developing more rigorous heuristics for model selection is desirable.

Notes

1. We reviewed the strategic groups papers published in the following journals using the ABI-Informs (Proquest) database: *Academy of Management Journal*, *Journal of Management*, *Journal of Management Studies*, *Management Science*, *Managerial and Decision Economics*, and *Strategic Management Journal*. In all, the search identified 73 papers ranging from a low of 2 (in *Management Science*) to a high of 42 (in *Strategic Management Journal*). Of the 73 papers, there were 45 papers that deductively identified strategic groups. Of these 45 articles, 30 used cluster analysis and another six used factor and cluster analyses combination. Thus, it is clear that cluster analysis, either used alone or in tandem with factor analysis, is the preferred data analytic technique used to identify strategic groups.
2. A less used but reasonable frequent method to identify strategic groups is to rely on researcher judgment and categorize firms as belonging to two or more strategic groups (Más-Ruiz *et al.*, 2005; Peng *et al.*, 2004). For example, in his study of 43 Indian manufacturing industries, Kumar (1990) identified two strategic groups: one for

multinational enterprises and the other for local firms. Our approach is more consistent with the main-stream research in strategic groups where data analysis reveals the strategic groups in an industry that can be used to assess the market structure of the industry, although the proposed methodology can be easily extended to accommodate such a priori classifications.

3. We used the Hoover's Online database to obtain information on the location of the headquarters of banks in order to identify the 111 banks.
4. As a contrast between the proposed procedure and the traditional two-step approach (factor, then cluster), we calculated the corresponding goodness-of-fit statistics associated with various MDPREF-cluster solutions (MDPREF is a form of weighted principal components analysis). Using the corresponding classification matrix defined by each clustering procedure as fixed (P) in our proposed clusterwise analysis together with the resulting MDPREF solution for the variable coordinates (X), we estimated the additive constant (b) and strategic and performance group coordinates (Y) optimally conditional on these fixed parameters. Our proposed procedure outperforms the nearest competitor (Ward method) by 57 percent with respect to percentage improvement in variance-accounted-for ($(0.347 - 0.221)/0.221$). Further, we compared the solution obtained by traditional cluster analysis (both K -Means and Ward) with those from the proposed method in terms of strategic and performance group membership. In both cases a four strategic-performance group solution had only 60 out of the 111 cases overlap (54.1 percent) in terms of strategic-performance group membership (a different 54.1 percent K -Means and Ward as they each resulted in different solutions with 72.9 percent overlap). Thus, practical suggestions to managers (in terms of which strategic/performance group they belong to and whom they compete with) are meaningfully affected by the data analytic technique used. Hence, not only are there difficulties in selecting amongst a number of possible clustering approaches in the traditional two-step approach, but, in addition, all are clearly sub-optimal in terms of explaining the structure in the input data.
5. ROE, NII use measures suggested by Alam and Brown (2006).
6. Refer to the computation in Cook: www.esa.doc.gov/reports/StructuralChange.pdf
7. CE, AE, CA, PTE and SE are measured according to Havrylchyk (2006).
8. In order to ensure that loan portfolios are of comparable quality, we subtracted loan loss provisions from the loans, referring to Grigorian and Manole (2002).
9. We do not include off-balance sheet items because we are focusing on domestic US commercial banks and this account negligent.
10. Prices of inputs are defined as labor expenses, depreciation expenses, and interest expenses divided by number of employees, fixed assets, and deposits, respectively. Refer to Havrylchyk (2006).
11. Labor is measured in the number of employees. Refer to Havrylchyk (2006).
12. We do not have access to data on provisions on lease loss or total loan and lease financing receivables.

References

- Alam, P. and Brown, C.A. (2006), "Disaggregated earnings and the prediction of ROE and stock prices: a case of the banking industry", *Review of Accounting & Finance*, Vol. 5 No. 4, pp. 443-63.
- Allen, L. and Rai, A. (1996), "Bank charter values and capital levels: an international comparison", *Journal of Economics and Business*, Vol. 48 No. 3, pp. 269-84.

- Amel, D.F. and Rhoades, S.A. (1988), "Strategic groups in banking", *Review of Economics and Statistics*, Vol. 70 No. 4, pp. 685-9.
- Amel, D.F. and Rhoades, S.A. (1992), "The performance effects of strategic groups in banking", *Antitrust Bulletin*, Vol. 37 No. 1, pp. 171-86.
- Ashenfelter, O. and Hannan, T. (1986), "Sex discrimination and product market competition: the case of the banking industry", *The Quarterly Journal of Economics*, Vol. 101 No. 1, pp. 149-74.
- Baird, I.S., Sudharsan, D. and Thomas, H. (1987), "Addressing temporal change in strategic group analysis: a three-mode factor analysis approach", *Journal of Management*, Vol. 14 No. 3, pp. 425-40.
- Barney, J.B. and Hoskisson, R.E. (1990), "Strategic groups: untested assertions and research proposals", *Managerial and Decision Economics*, Vol. 11 No. 3, pp. 187-98.
- Bharadwaj, A.S., Bharadwaj, S.G. and Konsynski, B.R. (1999), "Information technology effects on firm performance as measured by tobin's q", *Management Science*, Vol. 45 No. 6, pp. 1008-24.
- Brealey, R.A. and Myers, S.C. (1988), *Principles of Corporate Finance*, McGraw-Hill, New York, NY.
- Carroll, J.D. (1980), "Models and methods for multidimensional analysis of preferential choices (or other dominance data)", in Lantermann, E.D. and Feger, H. (Eds), *Similarity and Choice*, Hans Huber, Vienna, pp. 234-89.
- Caves, R.E. and Porter, M.E. (1978), "From entry barriers to mobility barriers: conjectural decisions and contrived deterrence to new competition", *Quarterly Journal of Economics*, Vol. 91 No. 2, pp. 241-62.
- Chung, K.H. and Pruitt, S.W. (1994), "A simple approximation of tobin's q", *Financial Management*, Vol. 23, pp. 70-4.
- Cool, K.O. and Schendel, D. (1987), "Strategic group formation and performance: the case of the US pharmaceutical industry, 1963-1982", *Management Science*, Vol. 33 No. 9, pp. 1102-24.
- Cool, K.O. and Schendel, D. (1988), "Performance differences among strategic group members", *Strategic Management Journal*, Vol. 9 No. 3, pp. 207-23.
- Coombs, C.H. (1964), *A Theory of Data*, Wiley, New York, NY.
- Desarbo, W.S. and Carroll, J.D. (1985), "Three-way metric unfolding via alternating weighted least squares", *Psychometrika*, Vol. 50, pp. 275-300.
- DeSarbo, W.S. and Grewal, R. (2008), "Hybrid strategic groups", *Strategic Management Journal*, Vol. 29 No. 3, pp. 293-317.
- DeSarbo, W.S., Di Benetto, T. and Song, M. (2007), "A heterogeneous resource-based view for exploring relationships between firm performance and capabilities", *Journal of Modeling in Management*, Vol. 2 No. 2, pp. 103-30.
- DeSarbo, W.S., Grewal, R. and Scott, C. (2008a), "A clusterwise bilinear multidimensional scaling methodology for simultaneous segmentation and positioning analyses", *Journal of Marketing Research*, Vol. 45, pp. 280-92.
- DeSarbo, W.S., Grewal, R. and Wang, R. (2008b), "Dynamic strategic groups: deriving evolutionary paths", working paper, Pennsylvania State University, University Park, PA.
- DeSarbo, W.S., Howard, D.J. and Jedidi, K. (1991a), "Multiclus: a new method for simultaneously performing multidimensional scaling and cluster analysis", *Psychometrika*, Vol. 56 No. 1, pp. 121-36.
- DeSarbo, W.S., Manrai, A.K. and Manrai, L.A. (1994), "Latent class multidimensional scaling: a review of recent developments in marketing and psychometric literature",

- in Bagozzi, R.P. (Ed.), *Advanced Methods of Marketing Research*, Blackwell, Cambridge, MA, pp. 190-222.
- DeSarbo, W.S., Wang, R. and Blanchard, S. (2008c), "Exploring intra-industry heterogeneity: the identification of latent competitive groups", working paper, Pennsylvania State University, University Park, PA.
- DeSarbo, W.S., Jedidi, K., Cool, K. and Schendel, D. (1991b), "Simultaneous multidimensional unfolding and cluster analysis: an investigation of strategic groups", *Marketing Letters*, Vol. 2, pp. 129-46.
- Dranove, D., Peteraf, M.A. and Shanley, M. (1998), "Do strategic groups exist: an economic framework for analysis", *Strategic Management Journal*, Vol. 19 No. 11, pp. 1029-44.
- Everitt, B.S. (1988), "A finite mixture model for clustering of mixed-mode data", *Statistics and Probability Letters*, Vol. 6, pp. 305-9.
- Ferguson, T.D., Deephouse, D.L. and Ferguson, W.L. (2000), "Do strategic groups differ in reputation?", *Strategic Management Journal*, Vol. 21 No. 12, p. 1195.
- Fiengenbaum, A. and Thomas, H. (1990), "Strategic groups and performance: the US Insurance industry", *Strategic Management Journal*, Vol. 11 No. 3, pp. 197-215.
- Fiengenbaum, A. and Thomas, H. (1993), "Industry and strategic group dynamics: competitive strategy in the insurance industry, 1970-84", *Journal of Management Studies*, Vol. 30 No. 1, pp. 69-97.
- Fiengenbaum, A. and Thomas, H. (1995), "Strategic groups as reference groups: theory, modeling and empirical examination of industry and competitive strategy", *Strategic Management Journal*, Vol. 16 No. 6, pp. 461-76.
- Fiengenbaum, A., Sudharshan, D. and Thomas, H. (1987), "The concept of stable strategic time periods in strategic group research", *Managerial and Decision Economics*, Vol. 8, pp. 139-48.
- Frazier, G.L. and Howell, R.D. (1983), "Business definition and performance", *Journal of Marketing*, Vol. 47 No. 2, pp. 59-67.
- Grigorian, D.A. and Manole, V. (2002), *Determinants of Commercial Bank Performance in Transition: An Application of Data Envelopment Analysis*, Vol. No. 02/146, International Monetary Fund, Washington, DC.
- Harrigan, K.R. (1985), "An application of clustering for strategic group analysis", *Strategic Management Journal*, Vol. 6 No. 1, pp. 55-73.
- Hatten, K.J. and Hatten, M.L. (1987), "Strategic groups, asymmetric mobility barriers, and contestability", *Strategic Management Journal*, Vol. 8 No. 4, pp. 329-42.
- Hatten, K.J. and Schendel, D.E. (1977), "Heterogeneity within an industry: firm conduct in the US Brewing industry 1952-71", *Journal of Industrial Economics*, Vol. 26 No. 2, pp. 97-113.
- Hatten, K.J., Schendel, D.E. and Cooper, A.C. (1978), "A strategic model of US Brewing industry: 1952-1971", *Academy of Management Journal*, Vol. 21, pp. 592-610.
- Havrylychuk, O. (2006), "Efficiency of the Polish banking industry: foreign versus domestic banks", *Journal of Banking & Finance*, Vol. 30 No. 7, pp. 1975-96.
- Houthoofd, N. and Heene, A. (1997), "Strategic groups as subsets of strategic scope groups in the Belgian brewing industry", *Strategic Management Journal*, Vol. 18 No. 8, p. 653.
- Ketchen, D.J. Jr and Shook, C.L. (1996), "The application of cluster analysis in strategic management research: an analysis and critique", *Strategic Management Journal*, Vol. 17 No. 6, pp. 441-58.

- Ketchen, D.J., Combs, J.G., Russell, C.J., Shook, C., Dean, M.A., Runge, J., Lohrke, F.T., Naumann, S.E., Haptonsthal, D.E., Baker, R., Berkstein, B.A., Handler, C., Honig, H. and Lamoureux, S. (1997), "Organizational configurations and performance: a meta-analysis", *Academy of Management Journal*, Vol. 40 No. 1, pp. 223-40.
- Kumar, N. (1990), "Mobility barriers and profitability of multinational and local enterprises in Indian manufacturing", *Journal of Industrial Economics*, Vol. 38 No. 4, pp. 449-63.
- Lee, R.P. and Grewal, R. (2004), "Strategic responses to new technologies and their impact on firm performance", *Journal of Marketing*, Vol. 68, pp. 157-71.
- Lewis, P. and Thomas, H. (1990), "The linkage between strategy, strategic groups, and performance in the UK Retail grocery industry", *Strategic Management Journal*, Vol. 11 No. 5, pp. 385-97.
- McGee, J. and Thomas, H. (1986), "Strategic groups: theory, research and taxonomy", *Strategic Management Journal*, Vol. 7 No. 2, pp. 141-60.
- McNamara, G., Deephouse, D.L. and Luce, R.A. (2003), "Competitive positioning within and across a strategic group structure: the performance of core, secondary, and solitary firms", *Strategic Management Journal*, Vol. 24 No. 2, pp. 161-81.
- Más-Ruiz, F.J., Nicolau-Gonzálbez, J.L. and Ruiz-Moreno, F. (2005), "Asymmetric rivalry between strategic groups: response, speed of response and ex ante vs. Ex post competitive interaction in the Spanish bank deposit market", *Strategic Management Journal*, Vol. 26 No. 8, pp. 713-45.
- Mehra, A. (1996), "Resource and market based determinants of performance in the US Banking industry", *Strategic Management Journal*, Vol. 17 No. 4, pp. 307-22.
- Nair, A. and Filer, L. (2003), "Cointegration of firm strategies within groups: a long-run analysis of firm behavior in the Japanese steel industry", *Strategic Management Journal*, Vol. 24 No. 2, p. 145.
- Nair, A. and Kotha, S. (2001), "Does group membership matter? Evidence from the Japanese steel industry", *Strategic Management Journal*, Vol. 22 No. 3, pp. 221-35.
- Nath, D. and Gruca, T.S. (1997), "Convergence across alternative methods for forming strategic groups", *Strategic Management Journal*, Vol. 18 No. 9, pp. 745-60.
- Nissim, D. (2003), "Reliability of banks' fair value disclosure for loans", *Review of Quantitative Finance and Accounting*, Vol. 20 No. 4, pp. 355-84.
- Osborne, J.D., Stubbart, C.I. and Ramaprasad, A. (2001), "Strategic groups and competitive enactment: a study of dynamic relationships between mental models and performance", *Strategic Management Journal*, Vol. 22 No. 5, pp. 435-54.
- Peng, M.W., Tan, J. and Tong, T.W. (2004), "Ownership types and strategic groups in an emerging economy", *The Journal of Management Studies*, Vol. 41 No. 7, pp. 1105-29.
- Peteraf, M. and Shanley, M. (1997), "Getting to know you: a theory of strategic group identity", *Strategic Management Journal*, Vol. 18, pp. 165-86.
- Porac, J.F. and Thomas, H. (1994), "Cognitive categorization and subjective rivalry among retailers in a small city", *Journal of Applied Psychology*, Vol. 79 No. 1, pp. 54-66.
- Porac, J.F., Thomas, H. and Baden-Fuller, C. (1989), "Competitive groups as cognitive communities: the case of Scottish knitwear manufacturers", *Journal of Management Studies*, Vol. 26 No. 4, pp. 397-416.
- Porter, M.E. (1979), "The structure within industries and companies' performance", *Review of Economics and Statistics*, Vol. 61, pp. 214-27.
- Reger, R.K. and Huff, A.S. (1993), "Strategic groups: a cognitive perspective", *Strategic Management Journal*, Vol. 14 No. 2, pp. 103-23.

- Rose, P.S. (1999), *Commercial Bank Management*, 4th ed., McGraw-Hill, Boston, MA.
- Ruiz, F.J.M. (1999), "Dynamic analysis of competition in marketing: strategic groups in Spanish banking", *International Journal of Bank Marketing*, Vol. 17 No. 5, pp. 233-45.
- Scherer, F.M. and Ross, D.R. (1990), *Industrial Market Structure and Market Performance*, Houghton Mifflin, Boston, MA.
- Serrano-Cinca, C. (1998), "From financial information to strategic groups: a self-organizing neural network approach", *Journal of Forecasting*, Vol. 17 Nos 5/6, pp. 415-28.
- Short, J.C., David, J., Ketchen, J., Palmer, T.B. and Hult, G.T.M. (2007), "Firm, strategic group, and industry influences on performance", *Strategic Management Journal*, Vol. 28 No. 2, pp. 147-67.
- Slater, P. (1960), "The analysis of personal preferences", *British Journal of Statistical Psychology*, Vol. 30, pp. 119-35.
- Slater, S.F. and Zwirlein, T.J. (1996), "The structure of financial strategy: patterns in financial decision making", *Managerial and Decision Economics*, Vol. 17 No. 3, pp. 253-66.
- Spender, J.C. (1989), *Industry Recipes: An Inquiry into the Nature and Sources of Managerial Judgment*, Basil Blackwell, Oxford.
- Sudharshan, D., Thomas, H. and Fiegenbaum, A. (1991), "Assessing mobility barriers in dynamic strategic groups analysis", *Journal of Management Studies*, Vol. 28 No. 5, pp. 429-38.
- Tang, M.J. and Thomas, H. (1992), "The concept of strategic groups: theoretical construct or analytical convenience", *Managerial and Decision Economics*, Vol. 13 No. 4, pp. 323-30.
- Thomas, H. and Venkatraman, N. (1988), "Research in strategic groups: progress and prognosis", *Journal of Management Studies*, Vol. 6 No. 6, pp. 537-56.
- Tobin, J. (1969), "A general equilibrium approach to monetary theory", *Journal of Money, Credit, and Banking*, Vol. 1, pp. 15-29.
- Tremblay, V.J. (1985), "Strategic groups and the demand for beer", *Journal of Industrial Economics*, Vol. 34 No. 2, pp. 183-97.
- Tucker, L.R. (1960), "Intra-individual and inter-individual multidimensionality", in Gulliksen, H. and Messick, S. (Eds), *Psychological Scaling*, Wiley, New York, NY.
- Vichi, M. and Kiers, H.A.L. (2001), "Factorial k-means analysis for two-way data", *Computational Statistics and Data Analysis*, Vol. 37 No. 1, pp. 49-64.
- Wedel, M. and DeSarbo, W.S. (1996), "An exponential-family multidimensional scaling mixture methodology", *Journal of Business & Economic Statistics*, Vol. 14 No. 4, pp. 447-59.
- Wedel, M. and Kamakura, W.A. (2000), *Market Segmentation: Conceptual and Methodological Foundations*, Kluwer, Boston, MA.
- Wernerfelt, B. and Montgomery, C.A. (1988), "Tobin's q and the importance of focus on firm performance", *American Economic Review*, Vol. 78 No. 1, pp. 246-50.
- Wiggins, R.R. and Ruefli, T.W. (1995), "Necessary conditions for the predictive validity of strategic groups: analysis without reliance on clustering techniques", *Academy of Management Journal*, Vol. 38 No. 6, pp. 1635-56.
- Zuniga-Vicente, J.A., Fuente-Sabate, J.M.D.L. and Rodriguez-Puerta, J. (2004), "A study of industry evolution in the face of major environmental disturbances: group and firm strategic behaviour of Spanish banks, 1983-1997", *British Journal of Management*, Vol. 15 No. 3, pp. 219-45.

Further reading

- Becher, D.A. (2005), "Incentive compensation for bank directors: the impact of deregulation", *The Journal of Business*, Vol. 78 No. 5, pp. 1753-77.
- Dahiya, S., Puri, M. and Saunders, A. (2003), "Bank borrowers and loan sales: new evidence on the uniqueness of bank loans", *The Journal of Business*, Vol. 76 No. 4, pp. 563-82.
- Kanagaretnam, K., Lobo, G.J. and Yang, D-H. (2005), "Determinants of signaling by banks through loan loss provisions", *Journal of Business Research*, Vol. 58 No. 3, pp. 312-20.
- Zhao, R.J. and Ye, Y. (2004), "The impact of SFAS No. 114 on the linear information dynamic for commercial banks", *Review of Quantitative Finance and Accounting*, Vol. 23 No. 4, pp. 313-28.

Appendix. Bank performance and strategy ratios*Performance variables**Profitability ratios*

- (1) Return on assets (ROA):
 - Annualized net income after taxes and extraordinary items as a percent of average total assets.
 - Net income generated per dollar of average assets invested during period. As a rule of thumb, an ROA of 1 percent is considered acceptable for most banks (DeSarbo and Grewal, 2008).
- (2) Return on equity (ROE)[5]:
 - annualized net income after taxes and extraordinary items as a percent of average total equity capital;
 - measures the return on each dollar of stockholders' equity;
 - normally large banks have smaller ROAs than smaller banks; and
 - return on equity represented by net income divided by total stockholders' equity.
- (3) Net profit margin (NPM):
 - net income/total current operating revenue.
- (4) Yield on earning assets (YEA):
 - Total interest income (annualized) as a percent of average earning assets. This ratio measures how much a bank is earning on its interest-earning assets.
 - YEA reflects general interest-rate levels, and, thus, can fluctuate over time. High YEA may indicate a high-risk portfolio of earning assets, particularly high-risk loans. Low YEA may indicate that the bank's portfolio has several problem loans or may indicate that the bank has overly conservative lending policies.
- (5) Net interest margin (NIM):
 - Net interest income as a percent of average earning assets (data 225).
 - Measures the difference between what a bank earns on its loans and investments (yield on earning assets) and what it pays on deposits and borrowings (cost of funding earning assets). Net interest margin (NIM) is the difference between the yield on earning assets and the rate paid on funds. NIM can vary with the particular business combination of the individual foreign banks.

Market valuation ratios

- (1) Tobin's q = (market value of equity + book value of liabilities)/(book value of assets) (Allen and Rai, 1996):

$$Q = \frac{\text{MVE} + \text{PS} + \text{DEBT}}{\text{TA}}$$

where, Q = Tobin's q . MVE = (closing price of share at the end of the financial year)*(number of common shares outstanding). PS = liquidating value of the firm's outstanding preferred stock. DEBT = (current liabilities – current assets) + (book value of inventories) + (long-term debt). TA = book value of total assets.

- (2) Market-to-book ratio (MBR) – market to book value of equity (www.dallasfed.org/banking/fis/fis9801.pdf):

$$\frac{\text{Stock price}}{\text{Book value per share}} = \frac{\text{Stock price}}{\text{Total book value/number of shares outstanding}}$$

- (3) Price-to-book ratio: stock price divided by book value per share.
 (4) Price-to-earnings ratio: stock price divided by earnings per share.
 (5) Price-to-assets: stock price divided by assets per share.
 (6) Price-to-deposits: stock price divided by deposits per share.

Efficiency ratios

- (1) Bank operating efficiency ratio (BOER)[6] (the ratio of noninterest revenue to expenses).
 (2) Sales to total assets (STA): total current operating revenue/total assets (efficiency in capitalizing on the assets).
 (3) Sales per employee (SPE): total current operating revenue/number of employees (efficiency in capitalizing on the human capital).
 (4) Cost efficiency ratio (CER):
- Noninterest expense, less the amortization expense of intangible assets, as a percent of the sum of net interest income and noninterest income.
 - This ratio evaluates the overhead structure of the bank. It is an overall indicator of how well the bank is managing its expenses (Ashenfelter and Hannan, 1986).
- (5) Cost per loan made (CTLM):
- formula: operating costs/number of loans made; and
 - purpose: indicates efficiency in disbursing loans (Ashenfelter and Hannan, 1986).
- (6) Cost of funding earning assets (CFEA):
- annualized total interest expense on deposits and other borrowed money as a percent of average earning assets; and
 - this ratio attempts to measure how much a bank is paying for its deposits and borrowings.
- (7) Noninterest income to earning assets (NIEA):

- annualized fee income and other income from services as a percent of earning assets; and
 - this ratio is a measure of a bank's other income sources (from fees, etc.).
- (8) Noninterest expense to earning assets (NEEA):
- Annualized non-interest expenses (e.g.: salaries and employee benefits, expenses of premises and fixed assets) as a percent of average earning assets.
 - This ratio is a measure of bank's operating expenses. For most banks, noninterest expenses far exceed noninterest income.
- (9) Net operating income to assets (NOIA):
- net operating income as a percent of average assets.
- (10) Technical efficiency (TE) refers to the ability to produce the maximum outputs at a given level of inputs, or ability to use the minimum level of inputs at a given level of outputs[7], and is measured as the total outputs (loans[8] + treasury Bonds[9]) over total inputs (deposits + fixed assets + labor[10,11]).

*Strategy variables**Asset quality ratios*

- (1) Noncurrent loans to loans (NCLL):
- we use long-term debt to approximate noncurrent loans; and
 - this ratio is an indicator of the percentage of problems loans in the bank's portfolio.
- (2) Loss allowance to loans (LAL)[12]:
- Allowance for loan and lease losses as a percent of total loan and lease financing receivables, excluding unearned income.
 - Indicates provisioning requirements on loan portfolio for current period.
 - This measures whether the loan loss allowance is adequate to cover potential loan losses. In other words, it is a general reserve kept by banks to absorb loan losses.
- (3) Loss allowance to noncurrent loans (LANL):
- allowance for loan and lease losses as a percent of noncurrent loans and leases; and
 - this is another measure of the adequacy of the loan loss allowance.

Capital adequacy (leverage) ratios

- (1) Equity capital to assets (ECA):
- Total equity capital as a percent of total assets.
- (2) Capital-assets ratios (CALR):
- Core capital = A bank's common equity (book value) plus qualifying cumulativeperpetual preferred stock plus minority interests in equity accounts of consolidated subsidiaries.
- (3) Equity capital ratio (EQRAT):
- EQRAT equity capital ratio: total equity capital as a proportion of GTA, where GTA equals total assets plus the allowance for loan and the lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). GTA equals total assets plus the allowance for loan and the lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans).

(4) Debt-equity ratio (DER):

$$\frac{\text{Total borrowing}}{\text{Book value}}$$

(5) Times-interest-earned (TIE):

$$\text{TIE} = \frac{\text{EBIT earnings before interest and taxes} + \text{Depreciation}}{\text{Interest}}$$

(6) Borrowing-to-total assets (BA):

$$\text{BA} = \frac{\text{Total borrowing}}{\text{Total assets}}$$

Liquidity ratios

(1) Liquid assets ratios (LAR):

- liquid assets/total assets.

(2) Asset liquidity ratios:

- Current ratio:
 - (1) current assets/current liabilities.

(3) Liability liquidity ratios:

- Net loans and leases to deposits:
 - (1) loans and lease financing receivables net of unearned income, allowances and reserves, as a percent of total deposits; and
 - (2) this ratio is an indicator of a bank's ability to support loan growth with deposits (Nissim, 2003).

Product ratios – loans

- LIS = gross loans/total investment securities.
- LA = gross loans/total assets.

Product ratios – deposits

- ISD = total investment securities/total worldwide deposits.
- LD = gross loans/total worldwide deposits.
- BD = total borrowings/total worldwide deposits.
- ID = total interest expense/total worldwide deposits.

JM2
3,3

About the authors

Wayne S. DeSarbo is the Smeal Distinguished Research Professor of Marketing in the Smeal College of Business at the Pennsylvania State University in University Park, PA. Wayne S. DeSarbo is the corresponding author and can be contacted at: Wsd6@psu.edu

Rajdeep Grewal is a Professor of Marketing and Dean's Faculty Fellow in the Smeal College of Business at the Pennsylvania State University in University Park, PA.

Heungsun Hwang is an Assistant Professor of Psychology at McGill University in Montreal, Canada.

Qiong Wang is an Assistant Professor of Marketing in the Smeal College of Business at the Pennsylvania State University in University Park, PA.

248

To purchase reprints of this article please e-mail: reprints@emeraldinsight.com
Or visit our web site for further details: www.emeraldinsight.com/reprints

Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.