A heterogeneous resource based view for exploring relationships between firm performance and capabilities

Wayne S. DeSarbo
Marketing Department, Smeal College of Business, Pennsylvania State University, State College, Pennsylvania, USA
C. Anthony Di Benedetto
Marketing Department, Fox School of Business Administration, Temple University, Philadelphia, Pennsylvania, USA, and
Michael Song
Department of Marketing, Henry W. Bloch School of Business and Public Administration, University of Missouri-Kansas City, Kansas City, Missouri, USA

Abstract
Purpose – The resource-based view (RBV) of the firm has gained much attention in recent years as a means to understand how a strategic business unit obtains a sustainable competitive advantage. In this framework, several research studies have explored the relationships between resources/capabilities and firm performance. This paper seeks to extend this line of research by explicitly modeling the heterogeneity of such relations across firms in various different industries in exploring the interrelationships between capabilities and performance.

Design/methodology/approach – A unique latent structure regression model is developed to provide a discrete representation of this heterogeneity in terms of different clusters or groups of firms who employ different paths to achieve firm performance *vis-à-vis* alternative capabilities. An application of the proposed methodology to a sample of 216 US firms were provided.

Findings – Finds that the derived four group latent structure regression solution statistically dominates the one aggregate sample regression function. Substantive interpretation for the findings is provided.

Originality/value – The paper contributes to the understanding of the performance effects of investing in capabilities in the RBV framework, which has previously been lacking, especially in the areas of information technology capabilities.

Keywords Resource management, Modelling, Competitive advantage, Company performance

Paper type Research paper

Introduction
The resource-based view (RBV) of the firm has been frequently utilized in the management literature over the past 20 years to understand the relationship between a business unit's resources/capabilities and its performance or profitability (Lippman and Rumelt, 1982, 2003; Wernerfelt, 1984; Rumelt, 1984; Barney, 1986, 1991; Bergh, 1998; Deephouse, 2000; Hult and Ketchen, 2001; Hansen *et al.*, 2004). Its emergence as a model

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of business unit performance traces back to the economic theory of firm growth developed by Penrose (1959) who argued that firms who possessed competencies (productive resources) and capabilities to best exploit those competencies (managerial resources) would be rewarded with the highest levels of growth and profitability. Day (1990, p. 38; 1994) has argued that a strategic business unit (SBU) can gain competitive advantage by developing the capabilities by which it can exploit its competencies. Though its acceptance has been somewhat controversial (Priem and Butler, 2001), the RBV has been described as the dominant model by which managerial researchers have explained differences among firms (Hoopes *et al.*, 2003). An SBU's capabilities are deeply rooted in routines and practices so are generally hard for competitors to imitate and, as a result, the SBU that develops appropriate capabilities can establish sustainable competitive advantage and maximize its growth and performance (Dierckx and Cool, 1989; Hoopes *et al.*, 2003). The relationship between resources/capabilities and performance is thus the basis of the RBV.

According to Helfat and Peteraf (2003), heterogeneity of capabilities and resources in a population of firms is one of the cornerstones of the RBV (Peteraf, 1993; Hoopes *et al.*, 2003). The RBV has been used to explain competitive heterogeneity as "enduring and systematic performance differences among relatively close rivals" (Hoopes *et al.*, 2003; Peteraf and Bergen, 2003). In particular, even the closest of rivals will have unique bundles of resources/capabilities (Barney, 1986; Wernerfelt, 1984; Peteraf, 1993). Furthermore, only some of these resources/capabilities may lead to sustained competitive advantage as they may have differential effects on actual performance. To be a source of advantage to a competitor, a resource or capability must be valuable (it can enable the SBU to improve its relative market position), rare (in short supply, or rare in terms of resource functionality), and isolated from imitation or substitution (immobile, and/or costly to replicate) (Peteraf, 1993; Peteraf and Bergen, 2003; Hoopes *et al.*, 2003). Since, SBUs will differ in terms of their possession of resources and capabilities that lead to sustainable advantage, as well as their differential utilization and effectiveness, their long-term performances will differ as well.

Some recent work has investigated the interrelationships between firm capabilities, environmental factors, and strategic type (DeSarbo *et al.*, 2006; Song *et al.*, 2007). Few research studies, however, have focused on how business unit management should make investments to develop capabilities in order to fit their strategies and improve financial performance. The literature suggests that strategic fit is an important precursor to improved performance (Zajac *et al.*, 2000). Relatively little research attention has been focused on the exact link between investments in specific capabilities and actual financial performance. For example, firms may make huge investments in building information technology (IT) capabilities in order to improve internal communication between functional areas (Davidow and Malone, 1992). Recent estimates place the US investment in IT at about $300 billion per year (Strassmann, 1997), and worldwide investment at $530 million, with an annual growth rate of about 10 percent (Willcocks and Lester, 1999). Given the size of these investments and their strategic importance to firms, it is very surprising that the relationship between IT capability investment and performance has not attracted more academic research.

The research objective of this study is to empirically identify the relationships between business unit capabilities and financial performance, taking into explicit account the various aspects of firm heterogeneity, and to use this understanding to make recommendations to business units on how to invest in capabilities in order to improve financial performance. According to the RBV, differences in firm resources and capabilities lead to heterogeneity in performance. Thus, different combinations of resources and/or capabilities may be exploited by SBUs in order to improve performance, and these different combinations define strategic categories of SBUs. We empirically investigate the relationships between firm capabilities and performance, while simultaneously modeling firm heterogeneity in a discrete fashion. We gather data on 216 SBUs/divisions located in the USA, representing selected industries. We use profitability (as measured by profit before tax divided by revenue) as the measure of performance of the SBUs, and devise a constrained latent structure regression methodology (based on such conditional finite mixture distributions) to explore inter-industry heterogeneity via discrete clusters or groups of firms. Our procedure simultaneously derives the groups/clusters or firms that account for the observed heterogeneity, solves for their size and membership, and also estimates group/cluster specific regression coefficients which denote the impact of capabilities on performance. Unlike forms of cluster analysis, we derive a set of information heuristics for determining the appropriate number of groups or clusters of firms. Unlike continuous hierarchical Bayesian approaches, we do not require multiple observations per SBU. In addition, *ad hoc* parametric assumptions concerning prior and hyper-prior distributions are not required as in hierarchical Bayesian schemes. The proposed procedure is sufficiently general enough to accommodate any sample of firms, any measure of performance, as well as any set of capabilities or resources. We find that a four-cluster/group solution derived optimally with the proposed methodology statistically dominates the aggregate sample solution (one group) suggesting that different groups of firms defined by different relationships between capabilities and resulting performance levels exist in our sample (i.e. heterogeneity). Our procedure therefore allows us to uncover differences in terms of capabilities and performance that would have been missed if heterogeneity in firm capabilities and performance had been ignored. *Post hoc* analysis is performed via ANOVA to dissect the sources of heterogeneity present in the application. The derived latent groups are profiled with respect to type of industry and strategic type. We conclude by discussing the four-group solution derived, and the implications for the RBV.

Theoretical background

The resource-based view

According to the RBV of the firm, a SBU has competencies that may improve performance in and of themselves. In order to take full advantage of these resources, however, the SBU must possess capabilities, defined as bundles of skills and knowledge, so that the SBU can deploy its competencies and coordinate its activities in such a way as to create sustainable competitive advantage (Lippman and Rumelt, 1982; Rumelt, 1984; Barney, 1986; Day, 1990, p. 38). Indeed, as mentioned in Hoopes *et al.* (2003) and Makadok (2001), since the original RBV publications by Wernerfelt (1984) and Barney (1986, 1991), a distinction has emerged in the RBV literature between capabilities and resources. According to Makadok (2001), a resource is an observable (but not necessarily tangible) asset that can be valued and traded. A capability is not observable (and not necessarily tangible), cannot be valued, and changes hands only as part of its entire unit. However, capabilities may be valuable in and of themselves (such as Wal-Mart's docking system), while others may be valuable mostly due to their ability to increase the value of other SBU resources (e.g. Nike's marketing capability boosts Nike brand equity) (Tripsas, 1997; Hoopes *et al.*, 2003). To the extent that these capabilities are difficult for competitors to imitate, they lead to long-term competitive advantage and performance (Dierckx and Cool, 1989; Hoopes *et al.*, 2003; Peteraf and Bergen, 2003; Lippman and Rumelt, 2003). Property rights, or costs of learning and development, can explicitly make capabilities hard to copy, but so can causal ambiguity (an SBU does not understand how a rival's capabilities lead to improved performance) (Hoopes *et al.*, 2003). SBUs with similar competencies, then, may not perform equally due to differences in their capabilities (Hitt and Ireland, 1986; Day and Wensley, 1988; Peteraf, 1993; Amit and Schoemaker, 1993; Peteraf and Bergen, 2003; Hansen *et al.*, 2004). Since, capabilities are difficult to imitate or substitute, it also follows that the SBU that most successfully cultivates these capabilities (i.e. that strategically adds capabilities which best complement the existing capability base) will outperform its competitors in the long run (Hitt and Ireland, 1986; Hunt and Morgan, 1995; Peteraf and Bergen, 2003; Hansen *et al.*, 2004).

It has been argued that the SBU's competencies, and the capabilities that allow the SBU to exploit competencies, are both SBU resources defined by Penrose (1959) as "productive resources" and "administrative resources," and this view is consistent with that of several other researchers from both the economics and management literatures (Alchian and Demsetz, 1972, p. 793; Makadok, 2001; Miller, 2003). Indeed, recent scholars have written that the utility of the RBV as a managerial tool can be effectively increased by shifting its focus to the decisions made by management in exploiting productive resources or core competencies (Hansen *et al.*, 2004).

Recent research in the RBV literature has used the RBV to explain heterogeneity (differences in resources/capabilities and therefore performance) among competitive rivals. For example, Hansen *et al.* (2004) develop a hierarchical Bayesian methodology (modeling continuous forms of heterogeneity which requires multiple observations per SBU and *ad hoc* parametric assumptions regarding prior and hyper-prior distributions) to examine the interrelationship between administrative decisions (not explicit capabilities or resources) and economic performance over time in order to capture individual firm differences. Note that rival SBUs will each have their unique bundles of capabilities, and since these capabilities allow them to exploit competencies and increase performance, it follows that rivals will differ in their performance as well (Barney, 1986; Peteraf, 1993: Hoopes *et al.*, 2003; Peteraf and Bergen, 2003). Exactly which capabilities have the greatest impact on sustainable competitive advantage has received some attention in the literature. According to Hoopes *et al.* (2003), capabilities must be valuable, rare, and isolated from imitation and substitution in order to provide sustainable advantage, and that of these, the most important qualities are value and inimitability. Peteraf and Bergen (2003) defined capabilities not by resource type, but in terms of resource functionality (i.e. what functions the capabilities serve), and argued that rareness in terms of resource functionality is also a source of competitive advantage.

Strategic business unit capabilities

Capabilities have been defined as "complex bundles of skills and accumulated knowledge that enable firms to coordinate activities and make use of their assets"

(Day, 1990, p. 38) to create economic value and sustain competitive advantage. While many capabilities have been cited in the existent literature (Day, 1990, 1994; Day and Wensley, 1988), several recent research studies have suggested that the following five capabilities are of particular relevance for studying sustainable advantage and long-term success (DeSarbo *et al.*, 2005, 2006; Song *et al.*, 2007): technology, market linking, marketing, IT, and management-related capabilities.

Technology capabilities such as technology development, product development, production process, manufacturing process, technological change forecasting, and logistics allow a firm to keep its costs down and/or to differentiate its offerings from those of competitors. Market linking capabilities include market sensing, channel and customer linking, and technology monitoring. These capabilities allow the firm to compete more effectively by early detection of changes in the market environment. Marketing capabilities such as skill in segmentation, targeting, pricing, and advertising allows the firm to take advantage of its market linking and technology capabilities and to implement marketing programs more effectively. IT capabilities permit the firm to diffuse technical and market information effectively throughout all relevant functional areas. Creative use of IT increases strategic flexibility and boosts the firm's financial performance and success with new products (Bharadwaj *et al.*, 1999). Management-related capabilities of all different types permit the firm to take advantage of all of the above capabilities, and include human resource management, financial management, profit and revenue forecasting, and others.

Heterogeneity

A variety of dynamic processes have been posited for explaining the heterogeneity present between firms with respect to resources and capabilities including the Teece *et al.* (1997) dynamic capabilities theory (Zott, 2002; Zollo and Winter, 2002) and the Helfat and Peteraf (2003) capabilities lifecycle theory. When adopting the RBV framework in relating capabilities/resources to firm performance, one has to be very specific in terms of defining heterogeneity, as it has both substantive and methodological meanings. Managerially, heterogeneity has been defined as "enduring and systematic performance differences among relatively close rivals" (Hoopes *et al.*, 2003). A similar definition is used in Peteraf (1993). To be consistent, we will adopt this initially as a working managerial definition. Note, however, such a conceptual definition does not render insight as to the underlying causes of heterogeneity or performance. To gain such additional insight requires a more specific framework which we develop below.

Methodologically, heterogeneity refers to a more general situation with respect to a specific model form. In this RBV context which examines the interrelationships between capabilities/resources and performance, let us assume a standard linear model in the form of:

$$y_i = \underline{X}_i \underline{b} + \varepsilon_i$$

where i indexes firms or SBUs in the sample observations, $\underline{X}_i$ contains the various capabilities (and/or resources) as independent variables, y_i is a performance variable of interest, and ε_i denotes an error term. Heterogeneity in this framework, i.e. differences in performance, can arise from at least three sources. Unexplained heterogeneity in this additive representation can be represented in terms of the variance of the error term σ^2.

For large variance, this suggests that firms with the same values of capabilities/resources in $\underline{X}$ may still realize different performance given other factors (e.g. environment) not pre-specified in $\underline{X}$. Alternatively, if each SBU possessed its own different $\underline{b}$ ($\underline{b}$), then such structural heterogeneity could result in different realizations of performance while pursuing the same resource/capacity strategy. The hierarchical Bayesian RBV approach of Hansen *et al.* (2004) is an effective way of dealing with such structural heterogeneity in a continuous manner, but the approach requires multiple observations per SBU and somewhat *ad hoc* parametric assumptions concerning the forms of prior and hyper-prior distributions. Finally, level heterogeneity refers to different amounts of resources/capabilities ($\underline{X}_i$) possessed by each of the firms or SBU's which also can lead to performance differences. Thus, one needs to identify the true source(s) of methodological heterogeneity in terms of a model form that can separate these various latent sources that can produce observed managerial heterogeneity.

The procedure proposed below will allow us to separate and identify these latent sources of methodological heterogeneity. At the managerial level, heterogeneity in performance may be observed, but the sources of it may be unclear or difficult to separate. For example, firms may show different levels in performance because they differ in terms of the capabilities they possess (level heterogeneity). Alternatively, they may have similar levels of capabilities, but may differ in terms of how well they exploit or utilize these capabilities to their advantage (structural heterogeneity). Or, there may be other unidentified sources of performance differences which transcend capabilities that are not included in the particular model (unexplained heterogeneity). The ways of identifying the sources of heterogeneity are therefore different and complementary. Managerial heterogeneity considers the specific case of performance differences among rivals, yet only states that the competitors' performances will differ. Methodological heterogeneity is defined more generally (i.e. not necessarily with respect solely to rival firms' performances), and relates to different causes underlying managerial heterogeneity. Our proposed methodology has the capability to identify these different sources of heterogeneity in performance, which at the managerial level are not easily identified or separated.

We now describe the technical details of the proposed constrained latent structure regression procedure devised to accommodate these different sources of heterogeneity in the relationships between capabilities and performance according to the RBV. Latent structure or finite mixture models are utilized in statistics and psychometrics as a way to model structural heterogeneity. In particular, our goal is to empirically derive clusters or groups of firms derived from observed data and simultaneously obtain the relationships between firm capabilities and profitability per each derived cluster. Model selection heuristics are developed which identify the appropriate number of clusters or groups. The model framework accommodates user specified constraints regarding the positivity of the estimated coefficients. Posterior probabilities of firm membership in each derived cluster or group are simultaneously estimated as well. Note, the proposed methodology is sufficiently generalized to accommodate the examination of any designated resources and/or capabilities with any specified measurement of firm performance.

A constrained latent structure regression methodology

Let: $k = 1, \ldots K$ derived cluster or group (unknown); $i = 1, \ldots I$ firms; $j = 1, \ldots J$ independent variables (here, capabilities); y_i = the value of the dependent variable for firm i (here, profitability); X_{ij} = the value of the jth independent variable for firm i (i.e. firm capabilities); b_{jk} = the value of the jth capability regression coefficient for cluster or group k; σ_k^2 = the variance term for the kth cluster or group; λ_k = the mixing proportion for the kth cluster or group.

DeSarbo and Cron (1988) modeled y_i as a finite mixture of conditional univariate normal densities:

$$y_i \sim \sum_{k=1}^{K} \lambda_k f_{ij}(y_i | X_{ij}, \sigma_k^2, b_{jk}) \tag{1}$$

$$= \sum_{k=1}^{K} \lambda_k (2\pi\sigma_k^2)^{-1/2} \exp\left[\frac{-(y_i - \underline{X}_i \underline{b}_k)^2}{2\sigma_k^2}\right], \tag{2}$$

where $\underline{X}_i = (X_j)$ and $\underline{b}_k = (b_j)_k$. Given a sample of I independent firms, the likelihood expression becomes:

$$L = \prod_{i=1}^{I} \left[\sum_{k=1}^{K} \lambda_k (2\pi\sigma_k^2)^{-1/2} \exp\left(\frac{-(y_i - \underline{X}_i \underline{b}_k)^2}{2\sigma_k^2}\right)\right] \tag{3}$$

or:

$$\mathrm{Ln}\, L = \sum_{i=1}^{I} \ln \left[\sum_{k=1}^{K} \lambda_k (2\pi\sigma_k^2)^{-1/2} \exp\left(\frac{-(y_i - \underline{X}_i \underline{b}_k)^2}{2\sigma_k^2}\right)\right]. \tag{4}$$

Given values of K, $\underline{y}$, and $\underline{X}$, the goal is to estimate λ_k, σ_k^2 and b_{jk} to maximize L or $\mathrm{Ln}\, L$, subject to:

$$0 < \lambda_k < 1, \tag{5}$$

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{6}$$

$$\sigma_k^2 > 0 \tag{7}$$

$$b_{jk} \geq 0. \tag{8}$$

The positivity constraint (not enforced on the intercepts) described in equation (8) is the methodological nuance in this manuscript that is added to the DeSarbo and Cron (1988) procedure given the a priori theoretical structure implied between specified firm capabilities ($\underline{X}$) and profitability ($\underline{y}$) in the application. Given the RBV theory which postulates positive effects for capabilities (it is indeed intuitive to believe that more of a capability or resource cannot possibly decrease performance), problems of multi-collinearity can often flip signs in such linear models. This is even more of a potential problem in clusterwise regression in which the sample size is sequentially partitioned into groups (DeSarbo and Edwards, 1996). Unfortunately, the addition of such constraints complicates the computational aspect of the proposed new methodology as shown in Appendix 1.

Thus, we use basically the same information/data as in traditional regression analysis, but now are able to simultaneously estimate discrete groups or clusters of firms, their sizes and membership, as well as the group level regression coefficients. Note that once estimates of $\lambda_k, \sigma_k^2,$ and b_{jk} are obtained within any iterate, one can assign each firm i to each cluster or group k (conditioned on these estimates) using Bayes' rule via the estimated posterior probability:

$$\hat{P}_{ik} = \frac{\hat{\lambda}_k f_{ik}(y_i | X_{ij}, \hat{\sigma}_k^2, \hat{b}_{jk})}{\sum_{k=1}^{K} \hat{\lambda}_k f_{ik}(y_i | X_{ij}, \hat{\sigma}_k^2, \hat{b}_{jk})}, \tag{9}$$

resulting in a fuzzy clustering of the I firms in K clusters or derived groups. Thus, one is interested in simultaneously estimating the mixing proportions (λ_k), regression coefficients (b_{jk}), variances (σ_k^2) and posterior probabilities of membership (P_{ik}), so as to maximize equation (3) or (4) subject to the constraints in equations (5)–(8), given a value of $K, \underset{\sim}{y},$ and $\underset{\sim}{X}$. The technical details of this estimation procedure are described in Appendix 1.

Note the various manners in which heterogeneity is captured within this modeling framework. Heterogeneity in mean performance levels is captured via the different intercepts estimated per derived group. Heterogeneity in the effectiveness of the various capabilities independent variables on performance (structural heterogeneity) is modeled by the different group specific regression coefficients. The group specific variance terms also provide a gauge of heterogeneity due to unexplained factors or error (unexplained heterogeneity). While the means of the capabilities are not explicitly modeled directly, there is no constraint placed on their respective group magnitudes so that ANOVA's can be performed post hoc to examine such mean differences in the X's (level heterogeneity). Thus, the proposed model can be utilized to partial out these different latent sources of heterogeneity for any empirical application. Nested model tests can be performed to test each for significance.

Note, since more recent work on the RBV have stressed the role of individual firm phenomena in relating capabilities and resources to performance (Lippman and Rumelt, 2003), one can obtain individual firm estimates of the various regression coefficients *vis-à-vis* the present methodology via:

$$b_{ij} = \sum_{k=1}^{K} \hat{P}_{ik}(\hat{b}_{jk}). \tag{10}$$

Model selection

To determine the number of clusters or derived groups (the value of K), the estimation procedure must be run for varying values of K. Bozdogan and Sclove (1984) discuss the use of Akaike's (1974) information criterion (AIC) for choosing the number of groups in mixture models. Accordingly, one would select K to minimize:

$$\mathrm{AIC}_K = -2 \ln L + 2N_K, \tag{11}$$

where N_K is the number of free parameters (in the full model):

$$N_K = (K - 1) + JK + K, \tag{12}$$

given no additional restrictions of any of the parameters. This AIC heuristic was utilized in DeSarbo and Cron (1988) for use in selecting K in their unconstrained latent structure regression methodology. Koehler and Murphree (1988) recommend the use of Schwarz's (1978) information criterion (BIC) due to the issues associated with the AIC's tending to sometimes select over-specified models (i.e. K too large). This is given by:

$$\mathrm{BIC}_K = -2\ln L + N_K(\ln I). \tag{13}$$

For empirical applications involving large samples, Bozdogan (1987) proposed the use of the consistent AIC (CAIC) as a heuristic that penalizes over-parameterization more strongly than does the AIC or the BIC. The CAIC statistic is computed as:

$$\mathrm{CAIC}_K = -2\ln L + N_K(\ln I + 1). \tag{14}$$

Note, the AIC, BIC, and CAIC measures, like other goodness-of-fit statistics, are heuristics for model selection (we also examine R_K^2). In addition to these statistics, we propose an entropy-based measure to assess the degree of fuzziness in group membership (when $K > 1$), based on the posterior probabilities:

$$E_K = 1 - (\Sigma_i \Sigma_k - P_{ik} \ln P_{ik})/I \ln K. \tag{15}$$

E_K is a relative measure that is bounded between 0 and 1. Given K clusters, $E_K = 0$ when all the posterior probabilities are equal for each respondent (maximum entropy). A value of E_K very close to 0 is cause for concern because it implies that all the centroids of the conditional parametric distributions are not sufficiently separated for the particular number of clusters or groups estimated.

Note, we have programmed this methodology to accommodate "external analyses" for comparative hypothesis testing and model comparisons. For example, one can test a derived estimated solution against any proposed alternative solution, and utilize one of the many information heuristics to designate which solution was "better" fit by the data. Here, for example, given an alternative, pre-specified clustering of firms, one can fix the posterior probabilities of membership, average them to obtain estimates of the mixing proportions, and perform one iteration of the M-step to obtain estimates of $\underset{\sim}{\sigma}$, and $\underset{\sim}{B}$ by given cluster or group. We will utilize this handy feature of the proposed methodology to compare our derived solution with a one-group solution (i.e. ignoring structural heterogeneity in firm capabilities affecting performance).

Data and measures

Our data were derived from a large-scale survey of 800 randomly selected US companies listed in Ward's Business Directory, Directory of Corporate Affiliations, and World Marketing Directory (DeSarbo *et al.*, 2005, 2006; Song *et al.*, 2007), following Dillman's (1978) recommendations for mail surveys. There were three distinct phases of data collection: a pre-survey, data collection on relative capabilities, and phone/fax interviews for SBU information on profits and revenues. In the first stage, a one-page survey and an introductory letter was sent to selected firms requesting their participation and offering a set of research reports as an incentive to cooperate. Firms were asked to provide a contact person for a chosen, representative SBU/division. Of the 800 firms contacted, 392 agreed to participate and provided the necessary contacts at the SBU/division level, and of these, a total of 216 firms provided complete data on relative capabilities and strategic type via questionnaire. Represented industries included: computer-related products; electronics; electric equipment and household appliances; pharmaceuticals, drugs and medicines; machinery; telecommunications equipment; instruments and related products; air-conditioning; chemicals and related products; and transportation equipment. Annual sales of sample SBUs ranged from $11 to 750 million, and SBU size ranged from 100 to 12,500 employees.

Respondents were required to rate their SBU on a series of 11-point capability scale items relative to their major competitors (0 – "much worse than our competitors" and 11 – "much better than our competitors"). The exact wording of the scale items is given in Appendix 2. An 11-point scale was used to obtain levels of agreement, where 0 represented "much worse than our competitors" and 10 "much better than our competitors." The five major capability areas were explicitly measured using all of these scales and have been appropriately validated in previous research studies (DeSarbo *et al.*, 2005, 2006; Song *et al.*, 2007).

Market linking capabilities

These include market sensing and linking outside the organization. Respondents were asked to rate their firms, relative to the top three competitors in their industry, on their capabilities in creating and managing durable customer relationships, creating durable supplier relationships with suppliers, retaining customers, and bonding with wholesalers and retailers.

Technological capabilities

These are capabilities relating to process efficiency, cost reduction, consistency in delivery, and competitiveness. Respondents rated their firms relative to the three major competitors on their capabilities in new product development, manufacturing processes, technology development, technological change prediction, production facilities and quality control.

Marketing capabilities

Using the Conant *et al.* (1990) marketing capabilities scale, respondents rated their firm's knowledge of customers and competitors, integration of marketing activities, skills in segmentation and targeting, and effectiveness of pricing and advertising programs, relative to the top three competitors in their industry.

Information technology capabilities

This scale measures the capabilities that help a firm create technical and market knowledge and facilitate communication flow across functional areas. Respondents rated the capabilities of their firm's IT systems relative to the competition on their ability to facilitate technology and market knowledge creation, to facilitate cross-functional integration, and to support internal and external communication.

Management capabilities

Respondents rated their firms, relative to their three major competitors, on their abilities to integrate logistics systems, control costs, manage financial and human resources, forecast revenues, and manage marketing planning.

Finally, in the last stage, all 216 SBUs were contacted via phone or fax correspondence to obtain data on profits before taxes and revenues. The dependent variable, profitability, was calculated as a percent profit margin by dividing SBU's profit before tax by SBU's revenue. Again, the proposed constrained latent structure regression methodology is sufficiently general to accommodate any dependent variable as well as any specification of independent variables (e.g. resources and/or capabilities).

DeSarbo *et al.* (2006) utilized aspects of this data to test the Miles and Snow (1978) strategic types framework against an empirically derived typology derived from a finite mixture structural equation methodology. These authors found that a dramatically different typology of strategic types could be empirically derived with much better statistical properties than the Miles and Snow traditional prospector, analyzer, defender, and reactor strategic types. Our objective is not to explicitly examine strategic types, but rather explore the nature of heterogeneity in the RBV framework amongst firms, and to decompose the nature of this heterogeneity in order to assess its latent source(s).

Empirical results

Aggregate sample K = *1 results*

First, the relationship between firm capabilities and profitability was estimated for the aggregate sample by multiple regression (Table I). This analysis is equivalent to performing the latent structure regression analysis for $K = 1$ groups as long as all the regression coefficients estimated remain non-negative. This aggregate regression model shows a significant overall fit ($F = 21.65$, $p < 0.01$; $R^2 = 0.34$). As shown in Table I, four of the five sets of firm capabilities were found to have significant, positive effects on profitability ($p < 0.01$). This is consistent with the expectation that these particular capabilities help firms achieve competitive advantage and, ultimately, success and profitability.

By examination of the coefficients in Table I, technology and IT capabilities were found to have the largest effect on profitability (coeff. = 5.31 and 3.47, respectively), with marketing and market linking capabilities having relatively lower, but still significant positive effects. Management capabilities, however, showed no significant effect (coeff. = 0.26). Thus, from the RBV framework, for this aggregate sample of 216 firms, technology and IT capabilities appear to impact profitability the most overall, followed by marketing and market linking capabilities.

Variable	Coefficient
Intercept	7.87*
Marketing	1.97*
Technology	5.31*
Market linking	1.89*
IT	3.47*
Management	0.26
SE	10.01
R^2	0.34
F	21.65*

Notes: $^*p < 0.01$

Table I. Aggregate sample $K = 1$ results

The constrained latent structure regression results

While the aggregate sample $K = 1$ solution presented above suggests that the technology-related capabilities are most closely related to performance (at least for this aggregate sample of firms), they leave unaddressed the issue of whether different capabilities are more critical to performance than others for different groups or clusters of firms. To investigate the various forms of heterogeneity discussed, we analyze this set of the US firms using the constrained latent structure regression methodology described earlier which models the observed relationships between capabilities and performance, and choose the "best" solution using the AIC heuristic as in DeSarbo and Cron (1988) (although the results are consistent across all information heuristics presented earlier).

Table II presents a summary of the various goodness-of-fit heuristics for our proposed constrained latent structure regression methodology as applied to this data set. The analysis was performed in $K = 1,2,3,4$, and 5 groups, with the AIC heuristic designating $K = 4$ derived groups as the "optimal" solution. The entropy statistic also confirms this solution as "best" as well in rendering good separation between the estimated conditional distribution centroids. In comparing the fit of the empirically-derived four group solution to that for the single-group solution (i.e., no heterogeneity in capabilities and performance) to assess any marginal improvement gained by accounting for heterogeneity in this sample, we note that we reject outright the aggregate sample regression function according to the AIC statistic. It is interesting to note that the corresponding $R^2 = 0.663$ for the four group solution is nearly twice that of the aggregate sample analysis. Thus, the model selection heuristics associated with the methodology is able to determine the extent of the heterogeneity that exists in this sample of firms and contrast it statistically vs the aggregate sample, no heterogeneity solution ($K = 1$).

The four group solution

Next, we examine the constrained latent structure regression estimates for the relative importance of firm capabilities by group for our empirically derived solution. Table III shows the breakdown of the 216 SBUs into the four groups. Groups 1-4 comprise 22, 13, 152, and 29 cases, respectively. That is, the largest derived cluster, Group 3, accounts for approximately 70 percent of the sample, while the remaining 30 percent is split among the three other groups. For Group 4, the highest-performing group, technology and IT capabilities have the greatest impact on profitability (coeff. $= 4.65$ and 8.56, respectively, $p < 0.01$). Group 4 is the most profitable of the derived clusters

Number of strategic types	AIC	Ln L	Entropy
1	1,622.7	−800.9	–
2	1,594.7	−774.9	0.404
3	1,587.2	−759.1	0.596
4 (optimal)	1,550.1	−728.5	0.701
5	1,562.6	−722.8	0.613

Notes: AIC – Akaike's information criterion; Ln L – log likelihood criterion; entropy – entropy-based measure (ranges from 0 to 1)

Table II.
Goodness-of-fit heuristics

Variable	Group 1	Group 2	Group 3	Group 4
Number of firms	22	13	152	29
Intercept	1.93**	2.28**	6.81**	13.23**
Marketing capability	3.81**	0.09**	1.13*	2.42
Technology capability	0.87**	0.82**	6.56**	4.65**
Market linking capability	1.72**	1.26**	3.84**	0
IT capability	3.64**	3.11*	0.32	8.56**
Management capability	0.91**	1.14**	0.04	0.05
Error variance	0.23	0.02	5.59	13.36
Mixing proportions	0.082	0.057	0.615	0.246
Mean profitability	2.300	2.292	7.181	18.176

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$

Table III. Our derived four group solution

(mean profitability = 18.176); these firms seem to be the most successful at turning their capabilities into profitability. Group 3, another relatively high-profitability cluster (mean profitability = 7.181), also shows a strong relationship between technology and profitability (coeff. = 6.56, $p < 0.01$). Market linking and marketing also have significant effects on profitability in Group 3 (coeff. = 3.84 and 1.13, respectively).

The results for Groups 1 and 2 are somewhat surprising since only for these two clusters is management capabilities significantly related to profitability. These two groups, both of which are less profitable on average than Groups 3 and 4, are relatively similar in terms of the relationships between capabilities and profitability (profitability = 2.300 and 2.292 for Groups 1 and 2, respectively). For Group 1, marketing capabilities are the most critical, followed by IT capabilities (coeff. = 3.81 and 3.64, respectively, $p < 0.01$). For Group 2, the two most critical capabilities are IT and market linking (coeff. = 3.11 and 1.26). In both cases, however, all five capabilities (including management capabilities) have significant effects on profitability at the $p < 0.05$ level or better. It is thus interesting to note how the aggregate $K = 1$ solution masks this structural heterogeneity captured in this $K = 4$ group solution.

In an effort to better describe these derived four groups of US firms, we conducted a number of analyses to examine mean differences between various items. Table IV depicts the various ANOVA results for each of the independent variables, as well as the dependent variable. What is of particular interest here is that the only significant differences that appear are those with respect to the dependent variable: profitability. There are no significant differences in mean values for any of the independent capability variables (no significant level heterogeneity). Thus, the underlying sources of heterogeneity captured by this methodology seems to be oriented around three facets of the data:

(1) the group differences concerning means of the dependent variable profitability as ascertained by these ANOVA runs;

(2) the differences in the regression coefficients (structural heterogeneity) reflecting the differential impact various capabilities have on profitability; and

(3) differences in unobserved heterogeneity as witnessed by the noticeable size and differences in the estimated group variance terms.

Table IV.
ANOVA tests for mean differences for the derived four group solution

		Sum of squares	df	Mean square	*F*	Sig
mkt	Between groups	1.039	3	0.346	0.343	0.794
	Within groups	213.976	212	1.009		
	Total	215.016	215			
tech	Between groups	1.090	3	0.363	0.360	0.782
	Within groups	213.928	212	1.009		
	Total	215.018	215			
mlink	Between groups	5.499	3	1.833	1.855	0.138
	Within groups	209.462	212	0.988		
	Total	214.961	215			
it	Between groups	1.664	3	0.555	0.551	0.648
	Within groups	213.349	212	1.006		
	Total	215.013	215			
man	Between groups	1.849	3	0.616	0.613	0.607
	Within groups	213.157	212	1.005		
	Total	215.005	215			
prof	Between groups	4,239.503	3	1,413.168	10.853	0.000
	Within groups	27,603.993	212	130.208		
	Total	31,843.496	215			

In other words, for this application and sample of 216 US firms, heterogeneity in performance is not accounted for by level heterogeneity: that is, the independent capability variables are not significantly different across the four groups. If these differences did exist, it would suggest that differences in relative performance are related to different levels of capabilities. Since, these differences are not significant, managerial heterogeneity in performance is accounted for by the differential effectiveness each of the capabilities have, rather than differential levels of the capabilities themselves. For Group 4, for example, the level of technology capability is insignificantly different from that of the other groups, but this group is apparently capable of applying or exploiting this capability relatively better than the other groups. Interestingly, type of industry had no significant impact in explaining group membership here.

To further profile these derived latent groups, we examined relationships between derived group membership with type of industry and strategic type (Miles and Snow, 1978). In the study, type of industry was collected and the various US firms were allocated to some eight different industry types. Based on field studies conducted in textbook publishing, electronics, food processing, and health care, Miles and Snow (1978) developed a strategic typology (prospectors, analyzers, defenders, and reactors) classifying firms according to enduring patterns in their strategic behavior. Prospectors are the leaders of change, competing by launching new products and uncovering market opportunities. Defenders maintain strong positions in existing markets or with existing products through resource efficiency, process improvements, and manufacturing cost cutting. Analyzers will defend their positions in some industries, but will often play a second-but-better role and selectively move into new product or market opportunities. All three of these "archetypal" strategic types perform well, as long as the strategies are implemented effectively, and outperform the reactor firms that do not show consistency in their strategic decisions. The Miles and Snow strategic typology has been popular in the management strategy literature for over two decades (Hambrick, 1983; Hitt and Ireland, 1986; McDaniel and Kolari, 1987; Ruekert and Walker, 1987; Conant *et al.*, 1990; Zajac and Shortell, 1989; Shortell and Zajac, 1990; Rajaratnam and Chonko, 1995; Dyer, 1997; Walker *et al.*, 2003). The data collected in the second stage of the data collection process was used to classify the 216 SBUs/divisions into the four Miles-Snow strategic types. The 11-item scale was developed by Conant *et al.* (1990). SBU strategic type (prospector, analyzer, defender, or reactor) was created using the "majority-rule decision structure" (Conant *et al.*, 1990)[1], with one modification: for an SBU to be classified as a prospector or a defender, it must have at least seven "correct" answers out of the 11 items. Using this procedure, we classified the 216 SBUs/divisions as follows: 62 prospectors, 79 analyzers, 59 defenders, and 16 reactors (DeSarbo *et al.*, 2005, 2006 for details).

Performing a contingency table analysis with the derived latent groups and type of industry with an associated χ^2 test revealed no significant relationships between these four derived latent groups and the eight industry types. When the same type of analysis was conducted with strategic types, however, a very significant relationship was identified for $p < 0.001$. Table V presents this cross-tabulation with associated raw counts, expected counts, row and column conditional distributions, joint distribution, and residuals with associated χ^2 test results. As noted, the χ^2 result suggests that the derived latent groups and Miles and Snow (1978) strategic types are not independent. A cursory examination of the residuals provides some indication of where this lack of independence is mostly derived from. Reactors appear to be under-represented in Group 3, but over-represented in Group 4. The opposite patter is seen with respect to defenders where there is an over-representation in Group 3 but an under-representation in Group 4. Analyzers appear under-represented in Group 4, whereas prospectors are over-represented in Group 4 and under-represented in Group 1.

The mapping displayed in Table V shows that the derived latent groups can be viewed as a very complicated mixture of the classic Miles-Snow strategic typology. When one conditions on the size of the derived latent groups and examines the conditional distributions in Table V (see the fourth entry in each cell), we see the following percentage modal compositions: Group 1 consists mostly of defenders and analyzers; Group 2 are mostly analyzers; Group 3 is nearly evenly split between defenders, analyzers, and prospectors; and, Group 4 is mostly prospectors and reactors. This latter finding is most surprising Group 4 is the highest performing, most profitable derived group and reactors are not traditionally recognized as such in the literature.

Discussion and conclusion

The RBV of the firm has been used in many research studies to explore the relationships between capabilities and performance results. To say that there is a relationship between capabilities and performance, however, is not sufficient. It is reasonable to ask which capabilities are most closely aligned with performance, as this may well differ across SBUs. Hambrick (1983) has implied that SBUs should continue to invest in those capabilities most beneficial to supporting their existing competencies and improving their performance. To extend this line of reasoning, we suggest that different patterns of capabilities may be associated with high levels of performance. We further argue that these patterns may be used as a basis for portraying heterogeneity via a grouping which can be empirically estimated.

In this paper, we devised a constrained latent structure regression methodology to derive empirically a four clusters. Based on our methodology, we can make

Table V.
Contingency table analysis of the four derived groups and Miles and Snow strategic types

			Derived latent class				
			1.00	2.00	3.00	4.00	Total
		*Strategic type * derived latent class crosstabulation*					
Strategic type	Reactor	Count	2	1	6	7	16
		Expected count	1.6	1.0	11.3	2.1	16.0
		Percent within strategic type	12.5	6.3	37.5	43.8	100.0
		Percent within derived latent class	9.1	7.7	3.9	24.1	7.4
		Percent of total	0.9	0.5	2.8	3.2	7.4
		Residual	0.4	0.0	−5.3	4.9	
	Defender	Count	7	3	46	3	59
		Expected count	6.0	3.6	41.5	7.9	59.0
		Percent within strategic type	11.9	5.1	78.0	5.1	100.0
		Percent within derived latent class	31.8	23.1	30.3	10.3	27.3
		Percent of total	3.2	1.4	21.3	1.4	27.3
		Residual	1.0	−0.6	4.5	−4.9	
	Analyzer	Count	10	7	57	5	79
		Expected count	8.0	4.8	55.6	10.6	79.0
		Percent within strategic type	12.7	8.9	72.2	6.3	100.0
		Percent within derived latent class	45.5	53.8	37.5	17.2	36.6
		Percent of total	4.6	3.2	26.4	2.3	36.6
		Residual	2.0	2.2	1.4	−5.6	
	Prospector	Count	3	2	43	14	62
		Expected count	6.3	3.7	43.6	8.3	62.0
		Percent within strategic type	4.8	3.2	69.4	22.6	100.0
		Percent within derived latent class	13.6	15.4	28.3	48.3	28.7
		Percent of total	1.4	0.9	19.9	6.5	28.7
		Residual	−3.3	−1.7	−0.6	5.7	
Total		Count	22	13	152	29	216

(continued)

Table V.

	Derived latent class 1.00	2.00	3.00	4.00	Total
Expected count	22.0	13.0	152.0	29.0	216.0
Percent within strategic type	10.2	6.0	70.4	13.4	100.0
Percent within derived latent class	100.0	100.0	100.0	100.0	100.0
Percent of total	10.2	6.0	70.4	13.4	100.0

χ^2 tests

	Value	*df*	*Asymp. Sig. (two-sided)*
Pearson χ^2	28.247[a]	9	0.001
Likelihood Ratio	26.048	9	0.002
Linear-by-linear association	0.915	1	0.339
N of valid cases	216		

Notes: [a]Six cells (37.5 pecent) have expected count less than 5. The minimum expected count is 0.96
Source: Miles and Snow (1978)

recommendations to managers on which capabilities should receive additional investment in order to maximize financial performance. We contribute to the understanding of the performance effects of investing in capabilities in the RBV framework, which as noted above has been lacking, especially in the areas of IT capabilities.

An important contribution of our model is that we are able to discern the sources of managerial heterogeneity among firms in our sample. As noted earlier, performance heterogeneity among rival firms has usually been defined in managerial terms (Hoopes *et al.*, 2003; Peteraf, 1993), referring to firm capabilities and their ensuing effects on firm performance. Left unanswered in this definition is the root cause of performance heterogeneity. Our methodology allowed us to separate out and identify three different possible sources of managerial heterogeneity. We found, for example, that the four derived groups differed greatly in terms of their profitability performances, and in terms of which capabilities were most closely related to performance. We did not, however, find significant differences across the firms in terms of the actual levels of capabilities possessed. This finding suggests that structural heterogeneity rather than level heterogeneity is most prevalent in the particular sample studied. Since, industry effects were found to be insignificant, this finding seems to be valid across all industries included in this sample. This finding is important to managers: it suggests that the simple possession, or acquisition, of additional capabilities (either by investing in external acquisition or internal development) is not necessarily the path to improved performance. Rather, the better-performing firms (i.e. those in Groups 3 and 4) seem to be able to exploit and utilize the capabilities they have better than the other firms. We examined relationships with our derived latent groups and type of industry and strategic types. Surprisingly, there were no significant relationship found between these four latent groups and type of industry suggesting that this form of heterogeneity is endemic across different industries. We did find a highly significant relationship between these four latent groups and the Miles and Snow (1978) typology, although the mapping from one to the other was by no means clear with substantial mixing.

There are certain limitations to our study. It is unclear whether the groups we estimate are generalizable to other industries, or other countries or geographical regions, not included in our study. It is possible that another solution, not necessarily with four groups, may dominate our empirically-derived solution in terms of fit for a different sample. We certainly do not claim that structural rather than level or uncertainty heterogeneity will always be the dominant source of performance heterogeneity. The appealing feature of our methodology is that it could be applied to any empirical sample including different kinds of industries (i.e. consumer-oriented, service-oriented, or inclusive of different geographical regions) to determine if heterogeneity exists there, and if so, what the sources seem to be empirically prevalent. Extensions of this study could focus on identifying the specific groups found in other environmental contexts. Nevertheless, we believe the constrained latent structure regression methodology presented here can be successfully used in understanding strategic decision making and performance outcomes in a wide range of contexts.

Note

1. In this procedure, an SBU is classified as a prospector if the majority of responses to the 11-item scale correspond to the prospector answers. A similar rule is used to classify SBUs into the other three strategic types.

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Appendix 1. The estimation algorithm

Estimation

One can frame the constrained estimation problem in equations (4)-(8) in terms of an E-M approach (Dempster *et al.*, 1977) in which we introduce non-observed data via the indicator function:

$$Z_{ik} = \begin{cases} 1 \text{ if firm } i \text{ belongs to derived cluster or group } k \\ 0 \text{ otherwise} \end{cases} \tag{A1}$$

We define the column vector $\underline{Z}_i = (Z_{il}, \ldots, Z_{ik})$, and the matrix $\underline{Z} = (\underline{Z}_i, \ldots, \underline{Z}_I)'$. It is assumed that the non-observed data Z_i are independently and identically multinomially distributed with probabilities $\underline{\lambda}$. The joint likelihood of y_i and $\underline{Z}_i$ (i.e. the "complete" data) is:

$$L_i(y_i, \underline{Z}_i, \underline{X}_i, \underline{B}, \underline{\sigma}) = \prod_{k=1}^{K} \lambda_k^{Z_{ik}} f_{ik}(y_i | \underline{X}_i, \underline{b}_k, \sigma_k^2)^{Z_{ik}}, \tag{A2}$$

or the complete ln likelihood over all firms:

$$\ln L_c = \sum_{i=1}^{I} \sum_{k=1}^{K} Z_{ik} \ln f_{ik}(y_i | \underline{X}_i, \underline{b}_k, \sigma_k^2) + \sum_{i=1}^{I} \sum_{k=1}^{K} Z_{ik} \ln \lambda_k. \tag{A3}$$

With the matrix $\underline{Z}$ considered missing, the modified E-M algorithm here amounts to iteratively alternating between an E-step (a conditional expectation step) and an M-step (a maximization step).

In the E-step, the expectation of $\ln L_c$ is evaluated over the conditional distribution of the non-observed data $\underline{Z}$, given the observed data $\underline{y}$, explanatory variables $\underline{X}$, and provisional estimates $(\underline{\lambda}^*, \underline{B}^*$, and $\underline{\sigma}^*)$ of the parameters $\underline{\lambda}, \underline{B}$, and $\underline{\sigma}$, respectively. This expectation is:

$$\begin{aligned} E_Z(\ln L_c; \underline{X}, \underline{\lambda} = \underline{\lambda}^*, \underline{B} = \underline{B}^*, \underline{\sigma} = \underline{\sigma}^*) = & \sum_{i=1}^{I} \sum_{k=1}^{K} E(Z_{ik}; \underline{X}_i, \underline{\lambda}^*, \underline{B}^*, \underline{\sigma}^* | y_i) \ln f_{ik}(y_i | \underline{X}_i, \underline{b}_k^*, \sigma_k^*) \\ & + \sum_{i=1}^{I} \sum_{k=1}^{k} E(Z_{ik}; \underline{X}_i, \underline{\lambda}^*, \underline{B}^*, \underline{\sigma}^* | y_i) \ln \lambda_k^*. \end{aligned} \tag{A4}$$

Using Bayes' rule and equation (A2), the conditional expectation of Z_{ik} can be computed as:

$$E(Z_{ik}; \underline{X}_i, \underline{\lambda}^*, \underline{B}^*, \underline{\sigma}^* | y_i) = \frac{\lambda_k^* f_{ik}(y_i | \underline{X}_i, \bar{b}^*, \sigma_k^*)}{[\Sigma_k \lambda_k^* f_{ik}(y_i | \underline{X}_i \underline{b}_k^*, \sigma_k^*)]} \tag{A5}$$

which is identical to the posterior probability P^{ik} defined in equation (9). Consequently:

$$E(Z_{ik}; \underline{X}_i, \underline{\lambda}^*, \underline{B}^*, \underline{\sigma}^* | y_i) = P_{ik}^*, \tag{A6}$$

where P_{ik}^* denotes the posterior probability of membership evaluated with provisional estimates $\underline{\lambda}^*, \underline{B}^*$, and $\underline{\sigma}^*$. Thus, in the E-step, the non-observed discrete data $\underline{Z}$ are replaced by the posterior probabilities computed on the basis of provisional parameter estimates, and equation (A4) becomes:

$$E_Z(\ln L_c; \underline{X}, \underline{\lambda} = \underline{\lambda}^*, \underline{B} = \underline{B}^*, \underline{\sigma} = \underline{\sigma}^*) = \Sigma_i \Sigma_k P_{ik}^* \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}_k^*, \sigma_k^*)] + \Sigma_i \Sigma_k P_{ik}^* \ln \lambda_k^*. \tag{A7}$$

In the M-step, $E_Z(\ln L_c; \underline{X}, \underline{\lambda} = \underline{\lambda}^*, \underline{B} = \underline{B}^*, \underline{\sigma} = \underline{\sigma}^*)$ is maximized with respect to $\underline{\lambda}, \underline{B}, \underline{\sigma}$ (subject to constraints in equations (5)–(8)) in order to obtain revised parameter estimates. These revised estimates are then used in the subsequent E-step to compute new estimates of the non-observed data $\underline{Z}$. The new estimate of $\underline{Z}$ is used in the subsequent M-step to arrive at new estimates of the parameters $\underline{\lambda}$, $\underline{B}$, $\underline{\sigma}$. The E-step and the M-step are successively applied until no further improvement in the ln-likelihood function is possible based on a specified convergence criterion.

In order to maximize $E_Z(\ln L_c; \underline{X}, \underline{\lambda} = \underline{\lambda}^*, \underline{B} = \underline{B}^*, \underline{\sigma} = \underline{\sigma}^*)$ in the M-step with respect to $\underline{\lambda}$, $\underline{B}$, $\underline{\sigma}$ subject to constraints in equations (5)-(8), we form an augmented function Φ, where:

$$\Phi = \Sigma_i \Sigma_k P^*_{ik} \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}^*_k, \sigma^*_k)] + \Sigma_i \Sigma_k P^*_{ik} \ln \lambda^*_k - \mu(\Sigma_k \lambda^*_k - 1), \tag{A8}$$

and μ is the corresponding Lagrange multiplier. The resulting maximum likelihood stationary equations are obtained by equating the first-order partial derivatives of Φ to zero. The stationary equations concerning λ_k are:

$$\frac{\partial \Phi}{\partial \lambda_k} = \Sigma_i \left(\frac{P^*_{ik}}{\lambda_k} \right) - \mu = 0. \tag{A9}$$

Summing both sides of equation (A9) over k yields:

$$\hat{\lambda}_k = \Sigma_i \frac{P^*_{ik}}{I}, \tag{A10}$$

where we have utilized the identity $\mu = I$ obtained by multiplying both sides of equation (A9) by λ_k and summing over k. The stationary equations concerning the parameters $\underline{B}$,$\underline{\sigma}$ can be derived as:

$$\frac{\partial \Phi}{\partial \underline{b}_k} = \Sigma_i P^*_{ik} \frac{\partial \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}^*_k, \sigma^*_k)]}{\partial \underline{b}_k} = \underline{0}, \tag{A11}$$

$$\frac{\partial \Phi}{\partial \sigma_k} = \Sigma_i P^*_{ik} \frac{\partial \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}^*_k, \sigma^*_k)]}{\partial \sigma_k} = 0, \tag{A12}$$

where:

$$\frac{\partial \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}^*_k, \sigma^*_k)]}{\partial \underline{b}_k} = [\underline{X}'_i (\sigma^*_k)^{-1} \underline{X}_i \underline{b}^*_k] \tag{A13}$$

$$\frac{\partial \ln[f_{ik}(y_i | \underline{X}_i, \underline{b}^*_k, \sigma^*_k)]}{\partial \sigma_k} = \frac{-1}{2\sigma_k} + \frac{(y_i - \underline{X}_i \underline{b}_k)^2}{2\sigma^4_k}. \tag{A14}$$

From equations (A11)–(A14), we can obtain the following closed-form expressions for the parameter estimates $\hat{\underline{B}}_k$ and $\hat{\sigma}_k$, using the respective likelihood equations:

$$\hat{\underline{b}}_k = \Sigma_i P^*_{ik} (\underline{X}'_i \underline{X}_i)]^{-1} [\Sigma_i P^*_{ik} (\underline{X}'_i y_i)], \tag{A15}$$

$$\hat{\sigma}^2_k = \left[\frac{\Sigma_i P^*_{ik} (y_i - \underline{X}_i \underline{b}^*_k)(y_i - \underline{X}_i \underline{b}^*_k)}{(I \lambda^*_k)} \right]. \tag{A16}$$

These expressions are intuitively appealing because they suggest that the parameter estimates are equivalent to weighted generalized least-squares estimates with the posterior probabilities P_{ik} as weights. Note that if we set $K = 1$ and estimate an aggregate pooled regression model in this framework, we get the traditional single equation regression results.

Although equation (A16) guarantees that $\sigma^2_k \geq 0, \quad \forall k$, there is no such assurance with equation (A15) involving the $\underline{b}_k$. As such, to enforce the positivity constraint in equation (8), a constrained optimizer must be utilized in each of the K weighted least-squares problems implied by equations (A12), (A13), and (A15). Here, we utilize a modification of the Lawson and Hansen (1972) procedure which follows directly from the Kuhn-Tucker conditions for constrained minimization. For a given $k = 1, \ldots K$, define:

$$\underline{h}_k = (h_i^k) = P_{ik}^{1/2}(y_i) \tag{A17}$$

$$\underline{E}_k = (E_{ij}^k) = (P_{ik}^{1/2} X_{ij}) \tag{A18}$$

We can then reformulate this estimation problem in terms of K non-negative least-squares problems:

$$\text{Minimize } \|\underline{E}_k \underline{b}_k - \underline{h}_k\| \quad \text{subject to } \underline{b}_k \geq 0 \quad \text{for } k = 1, \ldots, K, \tag{A19}$$

(excluding such constraints on intercepts) which trivially can be shown to conditionally (holding $\underline{X}$ fixed) optimize equation (A7). The algorithm, which is briefly outlined, follows directly from the Kuhn-Tucker conditions for constrained minimization. For a given k, we form the $I \times J$ matrix of "independent variables" $\underline{E}_k$, and the $I \times 1$ vector (acting as the dependent variable) $\underline{h}_k$. In the description that follows, the $J \times 1$ vectors $\underline{w}_k$ and $\underline{z}_k$ provide working spaces. Index sets P_k and Z_k are defined and modified in the course of execution of the algorithm. Parameters indexed in the set Z_k are held at the value of 0. Parameters indexed in the set P_k are free to take values greater than 0. If a parameter takes a non-positive value, the algorithm either moves the parameter to a positive value or sets the parameter to 0 and moves its index from set P_k to set Z_k. On termination, $\underline{b}_k$ is the solution vector and $\underline{w}_k$ is the dual vector:

(1) Set $P_k: =$ null, $Z_k: = \{1, \ldots, J\}$, and $\underline{b}_k := \underline{0}$.

(2) Compute the vector $\underline{w}_k := \underline{E}'_k(\underline{h}_k - \underline{E}_k \underline{b}_k)$.

(3) If the set Z_k is empty or if $w_{kj} \leq$ for all $j \in Z_k$, go to Step 12.

(4) Find an index a $a \in Z_k$ such that $w_{ka} = \max\{w_{kj} : j \in Z_k\}$.

(5) Move the index a from set Z_k to set P_k.

(6) Let $\underline{E}_P^{(k)}$ denote the $I \times J$ matrix defined by:

$$\text{Column } j \text{ of } \underline{E}_p^{(k)} := \begin{cases} \text{Column } j \text{ of } \underline{E}_k \text{ if } j \in P_k \\ 0 \text{ if } j \in Z_k \end{cases}$$

Compute the vector $\underline{z}_k$ as a solution of the least-squares problem $\underline{E}_P^{(k)} \underline{z}_k \cong \underline{h}_k$. Note that only the components $\underline{z}_{kj}$, $j \in P_k$, are determined by this problem. Define $\underline{z}_{kj} = 0$ for $j \in Z_k$.

(7) If $\underline{z}_{kj} > 0$ for all $j \in P_k$, set $\underline{b}_k := \underline{z}_k$ and go to Step 2.

(8) Find an index v $v \in P_k$ such that $b_{kv}/(b_{kv} - z_{kv}) = \min\{b_{kj}/(b_{kjv} - z_{kj}) : z_{kj} \leq 0, j \in P_k\}$.

(9) Set $Q_k := b_{kv}/(b_{kv} - z_{kv})$.

(10) Set $\underline{b}_k := \underline{b}_k + Q_k(\underline{z}_k - \underline{b}_k)$.

(11) Move from set P_k to set Z_k all indexes $j \in P_k$ for which $\phi_{kj} = 0$. Go to Step 6.

(12) Next k.

On termination, the solution vector $\underline{b}_k$ satisfies:

$$b_{kj} > 0, \quad j \in P_k; \tag{A20}$$

and:

$$b_{kj} > 0, \quad j \in Z_k, \tag{A21}$$

and is a solution vector to the constrained least squares problem:

$$\underline{E}_P^{(k)} \underline{b}_k \cong \underline{h}_k. \tag{A22}$$

The dual vector $\underline{w}_k$ satisfies:

$$w_{kj} = 0, \quad j \in P_k; \tag{A23}$$

and:

$$w_{kj} \leq 0, \quad j \in Z_k; \tag{A24}$$

where:

$$\underline{w}_k = \underline{E}'_k(\underline{h}_k - \underline{E}_k \underline{b}_k). \tag{A25}$$

equations (A20), (A21), (A23), (A24), and (A25) constitute the Kuhn-Tucker conditions characterizing a solution vector $\underline{b}_k$ for this constrained least-squares problem. equation (A22) is a consequence of equations (A21), (A23), and (A25). These 12 steps are then repeated for the next value of $k = 1, \ldots K$.

Hence, in the E-step we estimate P_{ik}, and in the M-step we estimate $\underline{\lambda}$, $\underline{\sigma}$ and $\underline{B}$. For specified initial values of these parameters, the conditional expectation (E-step) and the maximization phases (M-step) are alternated until convergence of a sequence of ln-likelihood values is obtained. Note, Dempster *et al.* (1977) provided a proof using Jensen's inequality that ln L_c increases monotonically, so convergence to at least a locally optimum solution can be proven using a limiting sums argument. Boyles (1983) and Wu (1983) provided a discussion of the convergence properties of the E-M algorithm. Unlike finite mixtures of other types of density functions, the parameters of finite mixtures of univariate normal densities are identified (Teicher, 1961, 1963; Yakowitz, 1970; Yakowitz and Spragins, 1968). Hennig (2000) discusses the identification problem in latent structure regression problems and derives sufficient conditions for three classes of such models. In essence, these conditions reduce to the fact that the matrix of independent variables in each of the derived groups must not be singular.

In addition, locally optimum solutions can plague such (and all) nonlinear models, especially those with small sample sizes and little separation of the centroids of the component distributions (Titterington *et al.*, 1985). Duda and Hart (1973) and Hosmer (1973, 1974) showed that such numerical difficulties diminish with larger sample sizes and reasonably separated distributions. Rational starts have been implemented using a quick clustering procedure, which accelerates convergence and diminishes difficulties with local optima problems. Upon convergence of the proposed algorithm for a specific number of clusters K, we obtain final estimates of the cluster proportions $\hat{\underline{\lambda}}$, regression parameters $\hat{\underline{B}}$, the variances $\hat{\underline{\sigma}}$, as well as the $\hat{P}_{ik}$ membership probabilities. The Cramer-Rao bound for the variance of the estimators is obtained via the negative inverse of the expectation of the Hessian matrix, which yields standard errors for all the free model parameters. Note, upon convergence, one may obtain estimates of individual firm regression coefficients by calculating:

$$b_{ij} = \Sigma_k P_{ik} b_{jk}. \tag{A26}$$

Appendix 2. The survey item coding record

Business capability items

The following is a set of possible business capabilities. Please evaluate how well or poorly you believe that this selected business unit performs the specific activities or processes the specific capabilities relative to your three major competitors. Please use the following response scale: 0 – much worse than the top three major competitors in the industry; 10 – much better than the top three major competitors in the industry (Table AI).

Variables: MK1-6; MLINK1-6; TE1-6; IT1-6; MR1-6: enter the number as circled.

	Much worse										Much better
MK1: Knowledge of customers	0	1	2	3	4	5	6	7	8	9	10
MK2: Knowledge of competitors	0	1	2	3	4	5	6	7	8	9	10
MK3: Integration of marketing activities	0	1	2	3	4	5	6	7	8	9	10
MK4: Skill to segment and target markets	0	1	2	3	4	5	6	7	8	9	10
MK5: Effectiveness of pricing programs	0	1	2	3	4	5	6	7	8	9	10
MK6: Effectiveness of advertising programs	0	1	2	3	4	5	6	7	8	9	10
MLINK1: Market sensing capabilities	0	1	2	3	4	5	6	7	8	9	10
MLINK2: Customer-linking (i.e. creating and managing durable customer relationships) capabilities	0	1	2	3	4	5	6	7	8	9	10
MLINK3: Capabilities of creating durable relationship with our suppliers	0	1	2	3	4	5	6	7	8	9	10
MLINK4: Ability to retain customers	0	1	2	3	4	5	6	7	8	9	10
MLINK5: Channel-bonding capabilities (creating durable relationship with channel members such as whole sellers, retailers, etc)	0	1	2	3	4	5	6	7	8	9	10
MLINK6: Relationships with channel members	0	1	2	3	4	5	6	7	8	9	10
IT1: IT systems for new product development projects	0	1	2	3	4	5	6	7	8	9	10
IT2: IT systems for facilitating cross-functional integration	0	1	2	3	4	5	6	7	8	9	10
IT3: IT systems for facilitating technology knowledge creation	0	1	2	3	4	5	6	7	8	9	10
IT4: IT systems for facilitating market knowledge creation	0	1	2	3	4	5	6	7	8	9	10
IT5: IT systems for internal communication (e.g. across different departments, across different levels of the organization, etc.)	0	1	2	3	4	5	6	7	8	9	10
IT6: IT systems for external communication (e.g. suppliers, customers, channel members, etc.)	0	1	2	3	4	5	6	7	8	9	10
TE1: New product development capabilities	0	1	2	3	4	5	6	7	8	9	10
TE2: Manufacturing processes	0	1	2	3	4	5	6	7	8	9	10
TE3: Technology development capabilities	0	1	2	3	4	5	6	7	8	9	10
TE4: Ability of predicting technological changes in the industry	0	1	2	3	4	5	6	7	8	9	10
TE5: Production facilities	0	1	2	3	4	5	6	7	8	9	10
TE6: Quality control skills	0	1	2	3	4	5	6	7	8	9	10
MR1: Integrated logistics systems	0	1	2	3	4	5	6	7	8	9	10
MR2: Cost control capabilities	0	1	2	3	4	5	6	7	8	9	10
MR3: Financial management skills	0	1	2	3	4	5	6	7	8	9	10
MR4: Human resource management capabilities	0	1	2	3	4	5	6	7	8	9	10
MR5: Accuracy of profitability and revenue forecasting	0	1	2	3	4	5	6	7	8	9	10
MR6: Marketing planning process	0	1	2	3	4	5	6	7	8	9	10

Source: Adapted from DeSarbo *et al.* (2006)

Table A1.

About the authors

Wayne S. DeSarbo is the Mary Jean and Frank P. Smeal Distinguished Professor of Marketing at the Smeal College of Business at the Pennsylvania State University at University Park, Pennsylvania. He has held similar chaired professorships at the Wharton School of the University of Pennsylvania, and the University of Michigan. He received his BS degree in economics from the Wharton School of the University of Pennsylvania. He has MA degrees in sociology, administrative science/OR, and marketing from Yale University and the University of Pennsylvania. He obtained his PhD in marketing and statistics from the University of Pennsylvania, and completed post doctorate work in operations research and econometrics there. He has published over 120 articles in such journals as the *Journal of Marketing Research*, *Psychometrika*, *Journal of Consumer Research*, *Journal of Mathematical Psychology*, *Marketing Science*, *Journal of Classification*, *Journal of Marketing*, *Management Science*, and *Decision Sciences*. His methodological interests lie in multidimensional scaling, classification, and multivariate statistics, especially as they pertain to substantive marketing problems in positioning, market structure, consumer choice, market segmentation, and competitive strategy. Wayne S. DeSarbo is the corresponding author and can be contacted at: wsd6@psu.edu

C. Anthony Di Benedetto is Professor of Marketing at the Fox School of Business Administration of Temple University, Philadelphia, Pennsylvania 19122.

Michael Song is the Charles N. Kimball, MRI/Missouri Endowed Chair in Management of Technology and Innovation at the Henry W. Bloch School of Business and Public Administration, University of Missouri-Kansas City, Kansas City, MO 64110. He is also Research Fellow and Advisory Professor of Innovation Management at the ECIS, Eindhoven University of Technology, The Netherlands.