STRUCTURING PRODUCT-MARKETS: AN APPROACH BASED ON CUSTOMER VALUE

Matthias Staat, University of Mannheim, Germany
Hans H. Bauer, University of Mannheim, Germany
Maik Hammerschmidt, University of Mannheim, Germany

ABSTRACT

We offer an efficiency-based approach to derive market partitions and respective benchmarks using Data Envelopment Analysis. Product efficiency is measured as an output to input value from the customer's perspective. Products offering a maximum customer value relative to alternatives represent benchmarks for different sub-markets. The framework is applied to data on compact cars.

THE CONCEPT OF MARKET STRUCTURING

Accurate market structuring is an essential condition for both strategic and tactical marketing decisions. Questions like "What is our market?" "Who are our competitors?" and "Which are our benchmarks?" need to be answered. By structuring markets one can gain considerable insight into the pattern of competition within the market and into the issue, which products can and should be compared against each other and which should not. Structuring implies to identify the composition and the contours of product subsets, which in turn requires drawing boundaries between them (Bauer and Herrmann 1995). This aim necessitates a market partitioning method.

Market partitioning is based on the assumption that a sales market is not made up of homogenous products but rather of separate product segments (sub-markets), which differ with regard to certain criteria. The idea is to group a pre-specified set of products in a way that products within a segment compete more heavily with each other than products belonging to different segments (Grover and Srinivasan 1987). The majority of the relevant research work holds that the criteria used for market partitioning should reflect demand-relevant product characteristics (Day, Shocker, and Srivastava 1979; Elrod 1991; MacKay, Easley, and Zinnes 1995).

According to a widely accepted definition, sub-markets are groups of products that are similar with respect to certain attributes and thus can be considered close substitutes (Bauer and Herrmann 1995). Several analytical methods have been proposed for the purpose of deriving product-market structures directly from choice data (DeSarbo et al. 1998; Grover and Srinivasan 1987; Ramaswamy and DeSarbo 1990). Such techniques typically utilize panel purchase data, which do not contain product attribute ratings or similarity measures. However, product features should be the underlying criteria when it comes to dividing the market into marketing relevant product segments.

Other approaches to define market boundaries do incorporate product characteristics but focus on either quality or performance-related attributes still others on price-related attributes (DeSarbo and Wu 2001; Lefkoff-Hagius and Mason 1993; Rao and Sabavala 1981) without integrating them into a higher order measure. The more recent research thrust in marketing has compiled strong evidence that consumers do not optimize on quality or on price separately but search for a favorable ratio of said dimensions (for an overview of such empirical studies see Huber, Herrmann, and Braunstein 2000). The quality-price-ratio or, more generally, the output-input ratio of a chosen product represents its value for a customer. This value reflects the customer's buying and consumption efficiency. Hence, the concept of customer value as a product's efficiency from the consumer's point of view should be incorporated when estimating product-market structures.

Market partitioning as defined above is only one element of insightful market structuring. In order to reveal competitive relationships and to gain information useful for product policy, benchmarking is needed as a second part of product-market structuring. In order to be instructive for marketing decisions, reference points in terms of benchmark product(s) must be identified.

As explained, from a customer value perspective products can be defined as bundles of input and output parameters. Benchmarks (best practices) are represented by products that offer the best ratio of outputs to inputs creating a maximum efficiency value to customers relative to the remaining products of the relevant sub-market. Benchmarking therefore means to identify best practice bundles and assessing all other products of a respective sub-market relative to this best practice. Only by examining segment benchmarks strengths and weaknesses can be derived in a truly competitive view.

To put these thoughts into a simplified formula we propose market structuring as a concept that combines market partitioning and benchmarking. Continuing our previous line of thought we introduce an integrative approach to market partitioning and benchmarking based on customer value and use a nonparametric technique known as Data Envelopment Analysis (DEA) as the methodological framework. Based on consumer ratings of several value relevant input- and output-attributes, we empirically apply our approach to the market for compact cars illustrating its potential for the derivation of competitive market structures.

Customer Value as a Basis for Market Partitioning and Benchmarking

From an economics and value based perspective consumers do not search for products with maximum quality or minimum price but seek to maximize the quality-price-ratio in the sense of value for money (Rust and Oliver 1994; Zeithaml and Bitner 2000). While forming their judgments about products consumers jointly consider both quality and non-quality-related dimensions within an economically oriented decision concept of "higher-order abstraction" (Sinha and DeSarbo 1998; Rust and Oliver 1994). This type of sophisticated, value sensitive purchasing behavior can be expected in competitive, especially electronically mediated markets. Instead of viewing value solely as a quality-price trade-off numerous authors demand a more systematic, multi-attribute operationalization (Sinha and DeSarbo 1998). Consequently, we conceptualize the two basic value dimensions in a multi-faceted way by measuring customer value (CV) as an efficiency ratio of weighted outputs and weighted inputs:

$$CV = \frac{\text{Outputs}}{\text{Inputs}} = \frac{\sum_{r}^{R} u_r y_r}{\sum_{i}^{I} v_i x_i}$$

Inputs x and respective weights v are indexed by i. They represent "investments" by the customer necessary to obtain and use a good. In addition to out-of-pocket cost such as price or running cost including insurance inputs could also be non-monetary sacrifices such as time, risk or search costs. Outputs y and respective weights u are indexed by r and represent "outcomes" of a product, i.e., performance attributes from which utility is derived (e.g., reliability, comfort, safety). CV is the customer's economic value derived from the product in the sense of an output to input efficiency value. It can be understood as the return on customer's investment. The analogy of CV and economic efficiency is obvious: the maximization of the output value achievable at alternative input levels is the underlying rationale of preference formation (Kamakura, Ratchford, and Agrawal 1988).

The general concept of CV models the customer's trade-off between all received outputs (positive consequences, utility) and all inputs (sacrifices, cost) across the entire process of purchasing and using the good. As a result, we obtain a broadly applicable measure of customer value, because all kinds of customer relevant input and output parameters can be included in our analysis, independent of scale level or dimensionality.

Although customer value has frequently been defined as a higher-order construct to evaluate products (Rust and Oliver 1996; Sinha and DeSarbo 1998), no empirical attempt has been made to structure product-markets on grounds of the customer value of their products. Conventionally, only perceived quality- or utility-related attributes are used without connecting them to price-variables within an input-output function. Standard methods for sub-market identification are multidimensional scaling or hierarchical cluster analysis (DeSarbo and Wu 2001; DeSarbo et al. 1998; MacKay, Easley, and Zinnes 1995; Rao and Sabavala 1981). Such methods enable researchers to infer, which products belong to one sub-market in terms of similarity with respect to particular quality criteria. Neither do they incorporate the value concept nor do they provide information about the products that represent best practice (benchmarks) in each of the several sub-markets.

AN INTEGRATED APPROACH TO VALUE-BASED BENCHMARKING AND MARKET PARTITIONING

Methodology

DEA is introduced as a nonparametric technique to assess the efficiency value of observed input-output structures, which can be companies, processes or – like in this paper – products. Efficiency results, measured on the basis of customer-relevant value parameters, are used as criteria to derive product-market partitions as well as intra-partition benchmarks. In this respect, our work extends existing marketing-related DEA studies (Doyle and Green 1991; Kamakura, Ratchford, and Agrawal 1988; Murthi, Srinivasan, and Kalyanaram 1996; Papahristodoulou 1997).

A rationale for choosing a nonparametric technique is the fact that it does not project the observed data into an inflexible scheme of fixed parameterization. Applying the same vector of parameter weights to all products exogenously would essentially apply one and the same global benchmark to all units (Bauer, Staat, and Hammerschmidt 2000). But it is in the nature of marketing that alternative value-creating product concepts (parameter-combinations) exist to serve consumer segments with corresponding preferences. Consequently, if an efficiency concept is to be meaningful it needs to calculate segment-specific efficiency scores.

In the sequel, we demonstrate that DEA is a powerful tool suited to structure markets in a systematic and differentiated way. Our approach achieves benchmarking and market partitioning endogenously by assigning individual weights to all parameters. Thus, different products can be rated as efficient, i.e., can serve as benchmarks.

DEA determines the degree of (in) efficiency of a product by measuring its distance to the efficient frontier. The efficient frontier (best value line) is made up of all identified "efficient" products. They all demand the lowest inputs for a given bundle of characteristics, at different scale levels and create a maximum customer value. These so called efficient peers represent benchmarks for all inefficient units. This principle adequately adopts consumer's buying strategy in the sense that the value of a product is judged not isolated but always in relation to relevant alternatives. Utilizing those types of inputs and outputs presented in section 2 the efficiency yielded by DEA represents relative customer value.

The customer value (CV) determination of a particular product that is being evaluated (denoted by the subscript "0") is formulated as a fractional programming problem:

Maximize

$$CV_0 = \frac{\sum_{r=1}^{R} u_r y_{r0}}{\sum_{i=1}^{I} v_i x_{i0}}$$

$$\text{(1)} \qquad \text{s. t.} \quad \frac{\sum_{r=1}^{R} u_r y_{rj}}{\sum_{i=1}^{I} v_i x_{ij}} \leq 1\,;\ j = 1, \ldots, J$$

$$u_r, v_i > 0;\ r = 1, \ldots, R;\ i = 1, \ldots, I.$$

where

R = number of outputs
I = number of inputs
y_{rj} = the value of the r^{th} output for the j^{th} product
x_{ij} = the value of the i^{th} input for the j^{th} product
u_r, v_i = positive weights given by the solution
J = number of products in the data set

This ratio of the weighted outputs and inputs (CV) is maximized under the restriction that no other product attains a score greater than 1 with the same weights that maximize the CV of the product that is being evaluated. Thus, all products with a CV of 1 offer a maximum relative customer value in the context of the products under investigation. CV is estimated only with respect to the specific competitive situation of the market.

Instead of applying the same vector of weights to the parameters for all products, as would be the case with standard approaches, DEA assigns an individual vector of weights to each product, optimally adjusted to each specific input-output structure (nonparametric approach). Maximum weights are attached to those variables where a product compares favorably and minimum weights are attached to those variables where it compares unfavorably. The weights contain important information about the customer value drivers. Parameters with high weights support the value of the product in question. With our flexible approach different strategies to create customer value (different combinations of customer relevant inputs and outputs) can be rated as efficient.

Furthermore, all products whose efficiency is estimated via the same benchmark(s) must have a comparable input-output-structure; otherwise different benchmarks would be identified as reference points. All products benchmarked via the same efficient peers can then be aggregated to one sub-market. By means of identifying different benchmarks jointly with similar inefficient products, we find "natural" market partitions and associated benchmarks simultaneously.

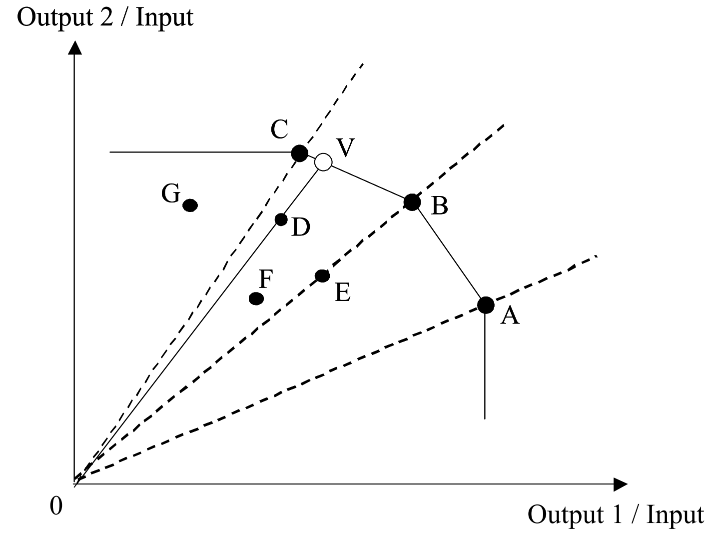
The results of the proposed integrative modeling of market partitioning and benchmarking are managerially useful in several ways. New products can be targeted to specific input-output combinations that are value maximizing in the sub-market the product belongs to. Also, the closer a product is to the benchmark the higher the preference to be expected.

Overview of the Model

First, we demonstrate our approach by mapping submarkets to the according best practice function. To keep matters simple, we assume an overall market with seven products (A to G) that can be described by two output-dimensions (comfort, safety) and one input-dimension (price). The outputs depicted are standardized on the input.

In order to consider these two value dimensions (quality-attributes related to price) simultaneously, a weighting scheme is needed. When applying exogenous weights the identification of the best value products depends solely on the vector of weights assigned (Staat and Hammerschmidt 2000). By flexibly weighting each product this dilemma is overcome. Now, more than one product strategy (A, B, and C in Figure 1) can be rated as efficient; in our example all three products create superior customer value by a different way of combining inputs and outputs. The products A to C can be interpreted as a specific value-benchmark, each representing a certain sub-market from a customer value point of view. They constitute the efficient frontier of the market reflecting the best value line. In contrast product F represents a suboptimal value strategy.

FIGURE 1
Illustrating Sub–Market Boundaries



As our stylized Figure 1 shows each cone that is formed by rays from the origin which intersect with an efficient product forms a sub-market; the rays being the sub-market boundaries. Products D, E, and F are located in the same direction as B and C, i.e., they create value in a similar way. Consequently, these products belong to the same sub-market. But, for instance, F is less successful in creating value because B and C dominate it. Thus, for consumers whose preferences are similar to the parameter weights assigned to B, C, and F, product F should not be the first best choice. In this example we can partition the overall market into three sub-markets. Homogeneity within a sub-market is not defined with respect to single parameters but with respect to the structure of value creation.

DEA estimates relative customer value for each market partition. Products D, E, and F are all evaluated using B and C because these are the efficient neighbors. Estimating intra-partition efficiency signifies that the efficiency value of D, E, and F is calculated relative to B and/or C but not, for instance, to A because this efficient peer is less comparable to D than to B or C.

The degree of inefficiency of a product is determined by measuring its distance to the origin relative to that of an efficient benchmark. For instance, the benchmark for E is product B as the nearest point on the efficient frontier. Therefore the inefficiency is calculated as the ratio of the distances of the two output combinations to the origin, i.e., $\overline{OE}/\overline{OB}$ (Charnes, Cooper, and Tone 2000).

Assuming a distance ratio of 0.8 implies a relative customer value of 0.8 for E. This value can be interpreted as follows: Product E offers only 80 percent of the outputs to the customer for the same investment as for product B. Put differently: From product B the customer receives 20 percent more comfort and safety for the same price. To reach the value maximal position, E would have to increase outputs by 20 percent without increasing price.

Estimation Algorithm

In order to simplify the optimization problem (1) above into an easily computable linear program a change of variables (Charnes, Cooper, and Rhodes 1978) is applied:

$$\text{(2)}\quad \begin{aligned} &\min_{\theta,\lambda,s^+,s^-} z_0 = \theta - \varepsilon s^+ - \varepsilon s^- \\ &\text{s.t.}\ \ Y\lambda - s^+ = Y_0 \\ &\theta X_0 - X\lambda - s^- = 0 \\ &\lambda, s^+, s^- \geq 0 \end{aligned}$$

$$\text{(3)}\quad \begin{aligned} &\max_{\mu,\nu} w_0 = \mu\, Y_0 \\ &\text{s.t.}\ \ \mu Y - \nu X \leq 0 \\ &-\mu \leq -\varepsilon \\ &-\nu \leq -\varepsilon \end{aligned}$$

Problem (3) (in vector notation) corresponds to equation (1) above and program (2) on the left is the primal of the same input-oriented problem. Here, efficiency is measured as the maximum input reduction possible for an inefficient product that has the same input-output-structure (strategy) as the corresponding benchmark on the efficient frontier. The efficiency score θ is augmented by input slacks s^- and output slacks s^+ multiplied by a non-Archimedean ε. It is thereby transformed into the so-called slack-augmented score z_0.

To recur to the example detailed in the previous section the input-oriented formulation implies that the value of product E could also be maximized by reducing necessary customer inputs by 20 percent, i.e., that the benchmark product B offers the same outputs for 80 percent of the inputs of E. This fraction of inputs is denoted by θ. It corresponds to our CV as defined in formula (1). For D, the reference unit V is made up of B and C. The factors λ in (2) denote the weights of the efficient peers in the reference unit for the product indexed with "0." Because V is located closer to C, which implies that D's structure is more like C's, λ_C is larger than λ_B. For E, the reference consists exclusively of B and $\lambda_B = 1$.

Slacks exist for all input parameters, for which an adjustment by the proportional factor 1 – does not suffice to reach an efficient value position. In (2), slacks for output parameters are labeled s^+, and those for inputs s^-. The latter indicate the variation of the parameter in question necessary in addition to the variation implied by the factor $1 - \theta$ in an input-oriented specification to match the corresponding value of the benchmark. Input parameters with zero slacks do contribute to the efficiency of a product and indicate its strengths. Parameters with non-zero slacks signify the weaknesses of the product; small variations w. r. t. to these parameters have no impact on the value position of the products. Slack parameters can be interpreted as determinants of inefficiency. By assessing strengths and weaknesses for each product, individual strategies to improve the product efficiency for customers can be derived.

EMPIRICAL APPLICATION

DEA-based market partitioning and benchmarking is now applied to an empirical example from the German compact car market. Our analysis includes 30 variants of the 11 best selling models of different automobile brands. Compact cars are bought with relatively little emotional involvement. On the output side the value of compact cars arises only to a minor extent from psycho-emotional or social attributes and to a major extent from technical-functional components. Thus, we can assume rational, cognitively highly involved buyers at least for a substantial fraction of consumers (Papahristodoulou 1997).

We use resale value after 4 years, reliability, safety, comfort, road performance, and sufficiency of the catalytic converter as outputs. Price and annual running cost serve as inputs. Instead of reporting on all 30 variants we show only minimum, maximum, and average values of the parameters:

Of the 30 analyzed model variants 40 percent are efficient. They do create maximum relative value for customers and thus form the efficient frontier. These efficient peers represent value benchmarks of different sub-markets because they achieve their position with a specific structure of the previously mentioned value-determining parameters. We find that 8 of the 11 models (brands) analyzed have at least one efficient variant in their line.

Due to space limitations we are unable to list the entire set of results, i.e., θ, λ, μ, and υ for each of the 30 variants.[1] We limit this illustration to four particular models, which suffices to understand the conclusions drawn in the sequel.

TABLE 1
Descriptive Statistics, German Automobile Drivers Club Member Survey, 1996

Parameters	Minimum	Maximum	Mean
Resale value in % of purchase price	0.30	0.56	0.38
Reliability (worst: 0.2; best: 1)	0.89	0.99	0.95
Safety (worst: 0.2; best: 1)	0.37	0.45	0.40
Comfort (worst: 0.2; best: 1)	0.30	0.50	0.40
Road performance in km p.a.	15.470	29.200	20.364
E3 Norm	No	Yes	57% Yes
Price in DM	23.100	36.980	26.766
Running cost p.a. in DM	2.509	4.727	3.202

TABLE 2
Parameter Data (for Selected Models)

Model	Price	Running Cost	Resale Value	Reliability	Road Performance	E3 Norm	Comfort	Safety
Honda Civic	26,890	3986	0.30	0.98	29200	yes	0.32	0.37
Toyota Corolla	23,990	2815	0.38	0.99	19310	no	0.38	0.41
VW Golf	25,700	2912	0.56	0.94	18280	no	0.45	0.41
Peugeot 306	29,000	3392	0.36	0.94	21070	no	0.40	0.38

The Toyota Corolla, for instance, offers below average or average outputs but requires the lowest investment in terms of price and running cost from the customer. The VW Golf (Volkswagen Rabbit), on the other hand, requires above average inputs but provides "market leading" performance on resale value and comfort. Both models create a maximum value with respect to the ratio of inputs and outputs but with entirely different value strategies. Therefore, both models represent benchmarks for different sub-markets ("value clusters").

Other car models like the Peugeot 306 are dominated. This model achieves less than the maximum relative value. The Corolla and the Civic are identified as nearest efficient neighbors for the Peugeot 306. They form its reference unit.

The significance of the efficient peers for the Peugeot 306 is reflected in the vector of weights, λ. The Corolla enters the reference unit with $\lambda_{Corolla} = 0.97$ and the Civic with $\lambda_{Civic} = 0.07$. The Corolla has a much higher importance for the reference unit of the Peugeot than the Civic, i.e., it is located much closer to the Peugeot than the Civic. The efficiency score θ is estimated at 0.9, implying that the Peugeot could create maximum customer value by reducing inputs by 10 percent (1-θ), provided that no slacks exist. But DEA has calculated non-zero slack for 5 out of the 8 parameters (see Table 3), which would hence have to be adjusted by more than 10 percent to achieve full efficiency.

Slack parameters represent critical value factors and can be interpreted as parameters whose performance is lagging considerably far behind the value benchmark. By means of the slacks s^+, s^- and the efficiency score θ, DEA provides exact indications of the extent by which each of the parameters would have to be adjusted.

According to the efficiency criterion, the Honda Civic, the Toyota Corolla, and the Peugeot 306 belong to the same sub-market. A second value segment derived is made up of the Mazda 323, the Hyundai Lantra, and again the Toyota Corolla and a third segment contains predominantly Opel Astra and VW Golf variants. Like unit B in Figure 1, the Corolla is located in a position where several sub-markets overlap defining the competitive market structure. Altogether the Corolla is located in the intersection of seven sub-markets, i.e., is comparable to the corresponding car models of these seven sub-markets. If comparability implies substitutability the Corolla is exposed to much more competitive pressure than for instance the Ford Escort, whose variants are all located within only one sub-market. While the Ford Escort can be considered as a successfully differentiated niche model, the Corolla is an "all purpose"-car, which almost competes against the entire compact car market.

TABLE 3
Efficiency Score θ and Virtual Multipliers[1] (for Selected Models)

Model	θ	Price	Running Cost	Resale Value	Reliability	Road Performance	E3 Norm	Comfort	Safety
Honda Civic	1.0	-0.37				0.299	0.127		
Toyota Corolla	1.0		-0.350		0.790		0.109		
VW Golf	1.0		-0.343	0.363			0.398		
Peugeot 306	0.9		-0.295			0.368		0.309	

By means of DEA we structured the 30 compact car variants into nine value-based sub-markets, whose benchmarks each reflect a successful strategy of maximizing value to customers. In addition to the three major sub-markets described above, six compact car models successfully established themselves as efficient products in proper niches. The sub-markets could be further aggregated by grouping them w. r. t. certain criteria such as price.

CONCLUSION

With DEA we propose a method to structure product-markets using the criteria of customer value. Since the method measures customer value in a relative way it provides sub-market specific value benchmarks. This has two main advantages. First DEA estimates intra-partition customer value. By means of the benchmarks sub-market boundaries can be identified. An overall market can thus be structured into several sub-markets (product segments). Each sub-market represents its own, specific approach towards the creation of customer value. Second, benchmarks provided for each identified product-market serve as target positions on which a customer value management should focus in order to create maximum value for customers and in turn for businesses.

DEA is a nonparametric technique estimating individual results for each product. The method does not operate with aggregated measures, i.e., does not provide an average value function that is identical for all units. Instead, DEA assigns an individual value function for each product, indicating a way for each product to improve (maximize) customer value. Of course, a better description of the specific advantages of the variants could be desirable, including non-technical output parameters such as design or brand image. The only reason of not doing so in the study at hand is in the nature of the used data set, which limited us to eight criteria.

ENDNOTES

[1] Virtual multipliers are part of the solution of the dual program (3). For all parameters with non-zero multipliers the slacks are zero and vice versa. The interpretation of the table may be given briefly, taking the Honda Civic as an example: The virtual multipliers for the Honda Civic are non-zero for price, road performance, and E3 Norm. Thus, only for these parameters slacks are zero, i.e., a variation by the proportional factor 1-θ is sufficient to reach the respective position on the efficient frontier. For the remaining five parameters, slacks exist. Therefore on these parameters the proportional variation has no effect for efficiency improvement.

[2] The complete results can be obtained from the authors upon request.

REFERENCES

Bauer, Hans H. and Andreas Herrmann (1995), "Market Demarcation," *European Journal of Marketing,* 29 (11), 18–34.

____________, Matthias Staat, and Maik Hammerschmidt (2000), "Product Controlling – An Approach Based on Data Envelopment Analysis," working paper W 45, Institute for Market-Oriented Management, University of Mannheim.

Charnes, Abraham, William W. Cooper, and Edoardo Rhodes (1978), "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research,* 2 , 429–44.

Cooper, William W., Lawrence M. Seiford, and Kaoru Tone (2000), *Data Envelopment Analysis.* Boston: Kluwer.

Day, George S., Allan D. Shocker, and Rajendra K. Srivastava (1979), "Customer-Oriented Approaches to Identifying Product-Markets," *Journal of Marketing,* 43 (Fall), 8–19.

DeSarbo, Wayne S., Youngchan Kim, Michel Wedel, and Duncan K.H. Fong (1998), "A Bayesian Approach to the Spatial Representation of Market Structure from Consumer Choice Data," *European Journal of Operational Research,* 111, 285–305.

____________ and Jianan Wu (2001), "The Joint Spatial Representation of Multiple Variable Batteries Collected in Marketing Research," *Journal of Marketing,* 38 (May), 244–53.

Doyle, J.R. and R.H. Green (1991), "Comparing Products Using Data Envelopment Analysis," *Omega,* 19, 631–38.

Elrod, Terry (1991), "Internal Analysis of Market Structure: Recent Developments and Future Prospects," *Marketing Letters,* 2 (August), 253–66.

Grover, Rajiv and V. Srinivasan (1987), "A Simultaneous Approach to Market Segmentation and Market Structuring," *Journal of Marketing Research,* 24 (May), 139–53.

Huber, Frank, Andreas Herrmann, and Christine Braunstein (2000), "Testing the Metric Equivalence of Customer Value," in *The Annual Conference of AMS 2000 Proceedings,* Hong Kong: Hong Kong University.

Kamakura, Wagner A., Brian T. Ratchford, and Jagdish

Agrawal (1988), "Measuring Market Efficiency and Welfare Loss," *Journal of Consumer Research,* 15 (December), 289–302.

Lefkoff-Hagius, Roxanne and Charlotte H. Mason (1993), "Characteristics, Beneficial, and Image Attributes in Consumer Judgements of Similarity and Preference," *Journal of Consumer Research,* 20 (June), 100–10.

MacKay, David B., Robert F. Easley, and Joseph L. Zinnes (1995), "A Single Ideal Point Model for Market Structure Analysis," *Journal of Marketing,* 32 (November), 433–43.

Murthi, B.P.S., Kannan Srinivasan, and Gurumurthy Kalyanaram (1996), "Controlling for Observed and Unobserved Managerial Skills in Determining First-Mover Market Share Advantage," *Journal of Marketing Research,* 33 (August), 329–36.

Papahristodoulou, Christos (1997), "A DEA Model to Evaluate Car Efficiency," *Applied Economics,* 29 (November), 1493–1508.

Ramaswamy, Venkatram and Wayne S. DeSarbo (1990), "SCULPTRE: A New Methodology for Deriving and Analyzing Hierarchical Product-Market Structures From Panel Data," *Journal of Marketing Research,* 27 (November), 418–27.

Rao, Vithala and Darius J. Sabavala (1981), "Inference of Hierarchical Choice Processes From Panel Data," *Journal of Consumer Research,* 8 (June), 85–96.

Rust, Roland T. and R.L. Oliver (1994), "Service Quality: Insights and Managerial Implications From the Frontier," in *Service Quality: New Directions in Theory and Practice,* Roland T. Rust and R.L. Oliver, eds. Thousand Oaks: Sage Publications, 1–20.

Sinha, Indrajit and Wayne S. DeSarbo (1998), "An Integrated Approach Toward the Spatial Modeling of Perceived Customer Value," *Journal of Marketing Research*, 35 (May), 236–49.

Staat, Matthias and Maik Hammerschmidt (2000), "Relative Performance Evaluation of Hospitals in Germany," in *Economics and Political Counselling Between Theory and Practice,* Ulrich Albertshauser and Hermann Knoedler, eds. Berlin: Verlag für Wissenschaft und Forschung, 221–53.

Zeithaml, Valarie A. and Mary J. Bitner (2000), *Services Marketing*, 2d ed. Boston: Irwin/McGraw-Hill.

For further information contact:
Matthias Staat
University of Mannheim
68131 Mannheim
Germany
Phone: +49.621.181.1894
FAX: +49.621.181.1893
E-Mail: matthias@pool.uni-mannheim.de