Evaluating perceptions-based marketing strategies

An agent-based model and simulation experiment

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Abstract

Purpose – To evaluate the comparative effectiveness of perceptions-based market segmentation strategies: to what extent do consumers' choice rules and the distinctness and variability of consumer preferences determine the success or failure of PBMS strategies?

Design/methodology/approach – The computer simulation is run on an artificial consumer market. Its firm and consumer agents enjoy a certain extent of autonomy and a limited capability of learning. Strategies for incorporating the choice information into the firms' segmentation schemes, consumers' brand choice rules, initial preference patterns and their variability over time are factors in the experimental design.

Findings – The market factors "brand choice rule" and "distinctness" and "adaptivity" of preferences significantly influence the profit performance of the segmentation and positioning strategies. The distinctness of the initial pattern of consumer preferences turns out to be least influential while the choice rule is most important.

Research limitations/implications – Computer simulation cannot replace analyses of real-world data. When, however, advanced explanatory models are made to fit to empirical data the results sometimes are disappointing (and then do not get published). Computer simulation on artificial markets assists in exploring the reasons for success or failure.

Practical implications – Boundedly rational consumers; product classes which are technologically homogeneous and subject to communications-driven differentiation; consumer preferences that are directly inaccessible and must be inferred from actual brand choice; consumers' perceptions and preferences evolving over time are realistic settings.

Originality/value – Controlling for conditions such as the consumers' choice rules and the distribution and variability of preferences in real markets demands a prohibitive research effort. No empirical study so far has tried to systematically relate the profit performance of marketing strategies to choice rules and preference distinctness and variability.

Keywords Perception, Marketing strategy, Modelling, Simulation

Paper type Research paper

Purpose

This experiment evaluates the comparative effectiveness of perceptions-based market segmentation (PBMS) strategies as proposed by Mazanec and Strasser (2000). PBMS is an alternative to response-based market segmentation (RBMS). RBMS derives the market segments directly from class-specific parameter estimates for the variables that are assumed to determine brand choice. If brand perceptions are analyzed the segments are constructed according to the direction and strength of relationship between the brand attributes perceived by the consumers and their brand choice.

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Unlike RBMS (Wedel and Kamakura, 1998; Wedel and DeSarbo, 2002) PBMS employs a two-stage analytical approach. While RBMS is certainly the prevailing paradigm a stepwise procedure still has its merits; examples are presented by Krieger and Green (1996) and Brusco *et al.* (2002). A parametric finite mixture model which is most typical for RBMS may not always be appropriate (Mazanec and Strasser, 2000, pp. 153–5, 160–3). Then a non-parametric sequential procedure may step in.

In PBMS the brand perceptions are analyzed in the first step and their relationships with choice are subsequently examined. There are several options for processing the choice data within PBMS. Their effectiveness is unclear and cannot be traced analytically. Therefore, different ways of incorporating the choice information into the segmentation scheme are considered as an experimental factor in the following agent-based design.

The experiment further addresses a simple research question that is yet hard to answer. To what extent do consumers' choice rules and the distinctness and variability of consumer preferences determine the success or failure of PBMS strategies?

Model builders both in marketing and economic theory have tended to ignore well-known properties of real markets and real consumer decision making that do not easily fit into closed form analytical treatment and parametric modeling. Consumer preferences, e.g. have been considered exogenous and fixed for quite long (Brenner, 1999). Only recently, evolutionary preferences captured by time-varying parameters have entered the mainstream of logit mixture modeling (Heilman *et al.*, 2000). Non-compensatory decision rules, though obstinately brought to attention (Bettman, 1971; Wright, 1975; Bettman *et al.*, 1998), rarely appear in the model builders' work results. West *et al.* (1997) who modeled non-compensatory rules with neural network (NN) methodology are a noteworthy exception. Only recently the Bayesian school of choice modeling started to consider consumers' non-compensatory decision rules (Gilbride and Allenby, 2004). Marrying multinomial logit with NN methodology also was the key to estimating non-linear utility functions in Hruschka *et al.* (2002). Andrews and Manrai (1998) incorporated choice simplification mechanisms into logit modeling.

This simulation experiment aims at boundedly rational consumers and product classes, which are technologically homogeneous and subject to communications-driven differentiation, advertising being the major means of competition. It acknowledges two levels of reality, one layer of advertising claims and perceived product attributes that are observable by the firms, and another layer of positions in latent brand space. Moreover, the consumer preferences are considered directly inaccessible and have to be inferred from actual brand choice. Consumers' perceptions and preferences evolve over time. The preferences modeled by consumers' ideal points may start off segment-specific or become diversified later on. Do variations of marketing intelligence and strategies matter in such a consumer world?

Controlling for conditions such as the consumer choice rule or the distribution and variability of preferences in real markets demands a prohibitive research effort. It seems that no empirical study so far has tried to systematically relate the profit performance of marketing strategies to choice rules or preference distinctness and variability. Given the limitations for field experiments the analysis will rely on simulation runs in an artificial market environment. This is an approach different from the simulation studies based on Monte Carlo experiments which are customary in logit choice model comparisons (Andrews *et al.*, 2002; Kanninen, 2002). The artificial market data are not directly generated from predetermined probability distributions. They rather evolve through the activities of the artificial firms and consumers.

The simulation is conceived as an agent-based exercise. The firm and consumer agents enjoy a certain extent of autonomy and a limited capability of learning. In terms of an agent typology they may be characterized as reactive but not yet smart (Nwana, 1996; Brassel *et al.*, 1997). The endowment of the agents must, of course, conform to the requirements of the experimental design.

The simulation environment used in this experiment is flexible enough to "switch on" the desired building blocks in a selective manner. This research strategy has been proven successful in game-theoretic studies pursuing related issues. Several authors inspired by Hauser and Shugan's (1983) Defender model included alternative preference distributions or preference overlap in their analyses (Ansari *et al.*, 1994; Gruca *et al.*, 2001). These authors also used simulation tools. But their "firm agents" enjoyed perfect market information, or, put more sharply, their optimizations are elaborated from an omniscient analyst's point of view. By contrast, the marketing agents acting in the following experiment are more like pilots navigating on a night flight and lacking radar guidance … a scenario claimed to be fairly representative of many real-world markets and managers.

The study proceeds as follows: the expected relationships between the experimental market factors and marketing strategy are made explicit in two sets of hypotheses. They determine the experimental design. The relevant characteristics of the artificial consumer market (ACM) are outlined next. Simulation results and conclusions come after. A non-technical presentation style is given priority whenever possible. In particular, the strategy agents are not described formally where a verbal description works with equal precision.

Experimental factors, hypotheses and design

Market factors

Cumulative profit serves as the dependent variable throughout the simulation runs. The three market factors selected for the experiment relate to the consumers' bounded rationality. A compensatory choice rule makes the consumer evaluate the trade-off among various brand attributes. It requires a more intense effort of information processing than a non-compensatory rule. Under a non-compensatory cognitive algebra the decision-maker just examines whether a buying alternative exceeds a satisfactory threshold on individual attributes. Conjunctive and disjunctive rules are prominent examples of non-compensatory schemes (Roberts and Lilien, 1993). A conjunctive rule demands satisfactory values on all product attributes; a disjunctive rule expects the product to exceed the satisfaction threshold on at least one attribute. In this experiment the market factor one is "choice rule" with the two levels "all consumer use the linear compensatory rule" and "a compensatory, conjunctive, and disjunctive rule gets employed by one third each".

Market factors two and three deal with consumer preferences. Factor two pertains to the stage of preference evolution. It determines the initial preference distribution at the beginning of each simulation run when the competing firms analyze the market response for the first time and decide on their strategies. Its two levels are named "distinct" because of its nicely separated segments and "rudimentary" or "indistinct" as no segment structure is discernible. Factor three regards the variability of preferences. Its levels are "fixed", i.e. no change at all, and "variable". The variability is smooth as the consumers gradually adapt the desired amount of product attributes to what they observe in the marketplace (Johnson *et al.*, 1995).

Marketing strategies

This experiment investigates combined segmentation/positioning strategies and their consequences for targeting and advertising content. Two basic types of such strategies are represented: mass marketing and selective operation. While mass marketers are merely needed to guarantee competition in each niche or segment, the research focus here is on selective market operation. The strategies, of course, are dependent on an appropriate method of analysis. Given the severe restrictions on consumer rationality in the experimental scenarios a parametric response model is unfeasible. There are no well-behaved utility functions, neither well-defined clusters for conventional cluster analysis, nor retrievable mixtures for parametric mixture regression models (Kamakura and Russell, 1989; Wedel and Kamakura, 1998; Wedel and DeSarbo, 2002) or even more elaborate Hierarchical Bayes models (Arora *et al.*, 1998; Otter *et al.*, 2002). Thus, the selective marketers proceed non-parametrically and pursue one of several perceptions-based marketing segmentation strategies as introduced by Mazanec and Strasser (2000). Actually, two variants of PBMS will be investigated. They are sets of rules serving as heuristics for the marketing agents on the artificial market.

Both PBMS strategies pursued by the firm agents exploit the market structure information hidden in the brands' perceptual profiles and the consumers' brand choice. The firm agents use vector quantization (VQ) as the underlying analytical tool. It partitions the brand profiles into subgroups. As these groups may but need not be equivalent to conventional clusters the term "perceptual classes" is more appropriate. An advanced VQ method named the Topology Representing Network (Martinetz and Schulten, 1994) has proven to serve this purpose excellently (Mazanec, 2001). However, the TRN, like its fellow clustering procedures, requires the analyst to decide on the number of classes to retain for the partition of brand profiles. In a simulation study with autonomous agents this decision must be automated. Therefore, a new dynamic version of a topology preserving NN was used. This dynamic topology representing network (DTRN) (Si *et al.*, 2000) applies a vigilance factor to continuously adjust the optimal number of classes during the data processing. The DTRN is briefly outlined in the Appendix.

Segmentation and positioning in strategy one ("all profiles")

(1) For PBMS strategy one all brand profiles are subject to the quantization into perceptual classes.

(2) The classes are then evaluated by the choices-to-profiles ratio, which favors those classes of brand profiles where a purchase was more likely to happen during the measurement period.

(3) As a second assessment criterion the "all profiles" agent considers its brand's share of purchases in each class.

(4) The “all profiles” marketing agent then selects those consumers for its target group who perceive its brand in a class of profiles exhibiting an above-average choice-to-profiles ratio and an above-average brand share.
(5) As long as the size of the target segment fails to exceed a “fair share” of the total consumer population (number of consumers/number of brands) the agent relaxes the two evaluation criteria in 5 percent steps and makes a reassessment plus reselection. This “flexibility of building up segments” corresponds to classic segmentation theory dating back to the 1970s (Wind, 1978).
An equally simple rule sequence works for the brand positioning.
(6) The “all profiles” agent compares the aggregate perceptual profile from the classes with an above-average choices-to-profiles ratio with the profile from the classes with a below-average ratio.
(7) It then selects the best discriminating product attributes for its advertising claims by lowering the selection limit in steps of 5 percent. The stepwise procedure ends when at least three claims have been identified.

It is a realistic assumption that surveys for measuring brand perceptions on real-world markets are carried out in greater intervals. Also the strategies use to persist for a little while. Therefore, the strategy agent utilizes the classification of brand profiles produced in period $t = 0$ and sticks to the derived strategy for six successive periods. A new analysis in period $t = 7$ leads to revising the evaluation of the perceptual classes. According to this update of market intelligence the target segment is adjusted and so is the selection of advertising claims. The revised strategy persists throughout the rest of the simulation run.

Segmentation and positioning in strategy two (“profiles chosen”)

(1) The PBMS strategy two agent relies on the classification of perceptual profiles that belong to the purchased brands only.
(2) It then determines the share of its brand in all these classes of the profiles actually chosen.
(3) The class with the highest share (“winner”) serves as a benchmark for computing the perceptual similarity to each of the other classes. Two evaluation criteria are available now: share and similarity.
(4) The target group is made up of consumers who associate the brand with a perceptual class both with an above average brand share and with an above average similarity to the “winner”. This guarantees a sympathy advantage for the brand and a small initial perceptual variation in the target segment.
(5) The “fair share” rule detailed in step (5) of the “all profiles” procedure also applies for the “profiles chosen” agent to prevent excessive customer erosion.
(6) For positioning purposes the “profiles chosen” agent aggregates and examines the differences between the profiles of the brands chosen and non-chosen by the individual consumers to identify the crucial product attributes.
(7) Analogous to the strategy one agent number two also extracts at least three best differentiating attributes with a 5 percent tolerance margin that may sometimes lead to four or five advertising claims.

Like its "all profiles" counterpart the strategy two agent also applies the same initial classification of brand profiles and the derived strategy during the six periods in the first half of the simulation run. The targeting decision based on an evaluation of the perceptual classes by exploiting the latest perceptual and brand choice information is updated in period $t = 7$ and so is the selection of advertising claims.

Mass marketers

The mass marketers cater to all individuals in the consumer population and do not differentiate their advertising messages. Consequently, they attempt to claim all popular product attributes for their brands and trust in the classical principle of "customer self-selection" (Frank *et al.*, 1972; Aaker and Myers, 1975). Like real markets the ACM penalizes advertising claim exuberance as the consumers learn significantly less per attribute compared to advertising exposures with a focus in message content.

Hypotheses

The experiment is guided by a number of hypotheses ordered in two sets *H1* and *H2*, which relate the independent strategy and market variables to the dependent variable "cumulative profit". The hypotheses flow from what can be expected about the market response caused by the experimentally varied market factors. The levels of a market factor like "consumer choice rule" correspond to the amount of fuzziness and unpredictability in purchase behavior. Tightening the rationality bounds means reducing the signal-to-noise ratio of the market response. This is expected to influence the effectiveness of the firms' marketing effort, also with such unsophisticated strategies as "all profiles" versus "profiles chosen":

H1.1. The profit performance of a joint segmentation/positioning strategy as represented by "all profiles" and "profiles chosen" is influenced by . . .

H1.1.a. the frequencies of compensatory and non-compensatory choice rules in the consumer population;

H1.1.b. the distinctness of the initial preference distribution; and

H1.1.c. the variability of the preferences owing to the consumers' adaptation of their aspiration levels.

In half the market scenarios the marketing agents on the ACM face an immature state of evolution of the consumer preferences. If this happens in addition to a consumer majority using satisficing rules and a non-compensatory cognitive algebra the market response delivers particularly ambiguous strategy advice:

H1.2. Profit performance is subject to an interaction effect between "choice rules" and "preference distinctness" as these factors enhance each other in their influence on strategy success.

The third factor "preference variability" does not affect the quality of the response data gathered in period $t = 0$ to develop the segmentation/positioning decisions. During the subsequent periods the adaptive preferences are expected to mitigate the effect of a suboptimal strategy. If, for example, some product attributes are not accentuated in any advertising claims the consumers come to think that their aspirations regarding these attributes are unrealistic and ought to be cut back:

H1.3. Profit performance is subject to an interaction effect between each of the two factors "choice rules" and "preference distinctness" and the third factor "preference variability" as adaptive preferences reduce the gap between product attributes desired and offered.

An analogous set of hypotheses *H2* considers the PBMS agents' profit performance in relation to each other:

H2.1-H2.3. The three market factors and their interactions addressed in *H1.1-H1.3* also influence the relative profit performance of a joint segmentation/positioning strategy as represented by "all profiles" and "profiles chosen".

Note that *H2* points to an expected difference of two alternative PBMS strategies. Measuring the strategy success in relative terms (i.e. as a profit share) eliminates the effect of a variable market volume. In the non-compensatory scenarios the market volume increases with the brand perceptions exceeding the aspiration thresholds. If both marketing strategies just perform uniformly better or worse compared to the mass marketers *H2* does not get support.

A priori there is no convincing rationale regarding superiority among the two strategies "all profiles" or "profiles chosen" under the various market scenarios. The former strategy relies on analyzing a broader database, while the latter restricts its observational material. The data lack reliability particularly in the beginning of the market evolvement and when non-compensatory decision-making prevails. In the early stage of market evolution substantial brand knowledge has not yet been disseminated. The threshold-driven rules prevent some consumers from purchasing any alternative. Nothing can be learned about their preferences. Such a threshold is missing in the compensatory scenario and a brand is bought though it may fall short of what the buyer desires. As the "profiles chosen" agent only analyzes the images of purchased brands it might benefit from a more meaningful representation of profiles in the "non-compensatory" scenario . . . the reasoning remains speculative, however, as there is no way of predicting the net effect of the various influences analytically. The question remains whether there is an overall winning strategy or one conditional on some market environment. It will be explored with the computer simulation tools.

Experimental setting

Market and strategy characteristics held constant. All simulation runs include four competing brands, i.e. two mass marketers and the two PBMS agents. The brands have no attraction potential other than what they promise by means of their attribute profiles. So there is no extra "name" effect leading to bias in measuring attribute assignments (Dillon *et al.*, 2001). Each of the four competing brands pursues the same kind of segmentation/positioning strategy in each run. One run lets the market evolve over 12 periods. Rather than in concrete time spans one period is defined by one advertising exposure and a purchase occasion (in real terms one may think of weeks or months). Each run is replicated 30 times. Each strategy agent has the same advertising budget of 1,000 units per period at its disposal. The agents charge the same and constant price of 100 and all consumers fix their reservation prices at 110. The market comprises a constant number of 300 consumers; hence the upper limit of the market volume in dollar sales is 30,000.

Design. Figure 1 shows the full-factorial design with 2^3 combinations. Given the hypotheses in *H1* on absolute profit and *H2* on relative profit performance the dependent variable is appropriately defined as cumulative profits (*H1*) or as the difference in shares of the cumulative profits (*H2*) between the brands no. 3 ("all profiles") and no. 4 ("profiles chosen").

Each of the 30 replications of each of the eight simulation runs starts with a new randomly generated initial configuration of brand positions and ideal points. Figures 2 and 3 show two $t = 0$ situations, one for distinctly segmented preferences and one undifferentiated case. As Figure 2 shows for the attitudinal dimensions 1 and 2

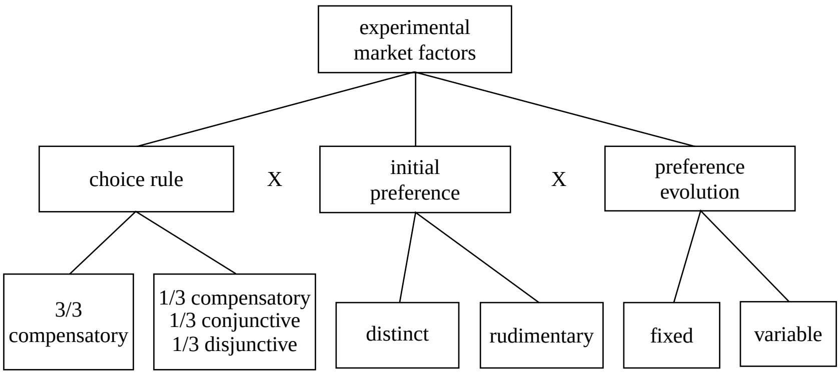

Figure 1.
Experimental design

loadings (*), facscores (+), tecscores (0) prefs (.) in latent space 1vs 2

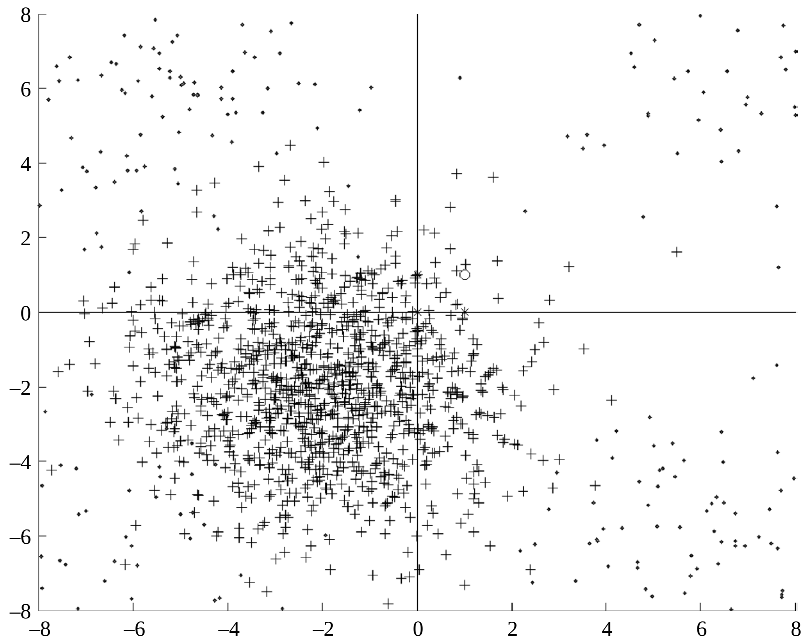

Figure 2.
Distinct preferences in $t = 0$

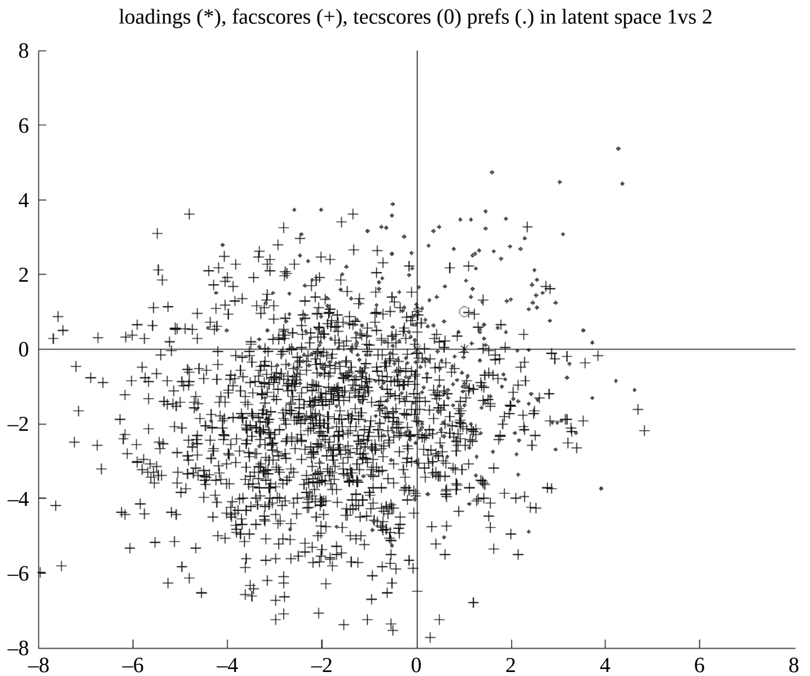

Figure 3.
Indistinct preferences in $t = 0$

the consumers desire an advanced position in just two dimensions. Each pair of desired product dimensions is represented with equal frequency in the "distinct preferences" setting. If the preferences represented by the consumers' ideal points are also variable this nice configuration may be destroyed pretty soon.

The simulation environment

Advertising response and perceptual dynamics

Figure 4 shows an impression of the concepts involved in the ACM. The consumer model of the ACM simulation environment expands the latent brand space paradigm originally introduced in the most influential book on buyer behavior ever written (Howard and Sheth, 1969) and further propagated until these days (Engel *et al.*, 1973; Howard, 1977; Mazanec, 1978; Kroeber-Riel, 1980; Bagozzi, 1986; Roberts and Lilien, 1993; Myers, 1996; Dillon *et al.*, 1985 for some measurement implications of the three-way data involved). The ACM distinguishes between the observable brand attributes, which are available to the firms as binary yes/no reactions (such as in the Unilever Brand Health Check administered in European countries), and the underlying latent attitude dimensions. The ACM models the brand perceptions on three levels: latent attitudinal dimensions, item response generating probabilities and redundant sets of observable indicators of the latent dimensions.

The marginally decreasing advertising response function (1) complies with recommended modeling practice (Hauser and Shugan, 1983). It establishes the connection between the marketing agents' allocation of their communication budgets to the target groups and the consumers' learning of brand attributes:

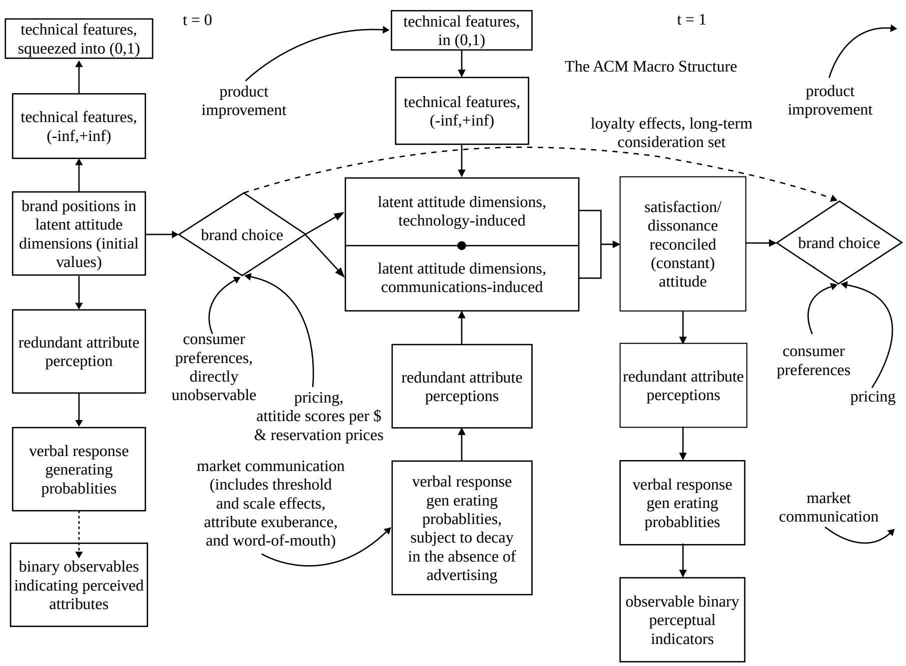

Figure 4.
The ACM macro structure

$$\mathbf{M} = \pi - \exp(-\rho \mathbf{w}\mathbf{o}') \cdot^{*} \mathbf{S} \tag{1}$$

where:

$$\mathbf{M} = \begin{pmatrix} \mathbf{M}_1 \\ \cdots \\ \mathbf{M}_B \end{pmatrix}$$

is a stacked matrix of dimensionality $(B \times C) \times V$ with $\mathbf{M}_b$ standing for brand b and $m_{(b,c),v}$ expressing the change factor for the probability that consumer $c = 1, \ldots, C$ attributes the product characteristic $v = 1, \ldots, V$ to brand $b = 1, \ldots, B$; exp(.) denotes element-wise exponentiation, the prime indicates the transpose and the $\cdot^{*}$ operator stands for an elements-by-elements product; π is the persistency parameter with a feasible range of $0.6 < \pi < 0.8$ (set to 0.7). ρ is the responsiveness parameter with recommended values of 2 or 3 (set to 2). $\mathbf{w}$ is a $(B \times C) \times 1$ vector of the relative advertising "impact" directed to consumer c by brand b; the impact depends on the advertising budget, the number of consumers in the target audience (taking a non-linear scale effect into account), and the number of claims (with a non-linear penalty for attribute exuberance). $\mathbf{o}' = (1\ 1 \ldots 1)$ is a row vector of ones with V entries. $\mathbf{S}$ is a $(B \times C) \times V$ matrix of zeros and ones indicating the attributes the marketing agent has included as claims in its advertising message; an indirect learning effect is added to $\mathbf{S}$ by increasing those zero elements not advertised but semantically associated with another advertised one.

As a result of (1) the amount of the perceptual change factor varies between a decay of $-\pi$ for a non-exposure or irrelevant claim and π as the upper limit due to a relative impact of 1. If an element in $\mathbf{M}$ is non-positive, the relative budget impact does not pass the effectiveness threshold implicitly set by the parameters π and ρ and thus cannot prevent decay.

The time index has been suppressed. In (2) and (3) it is needed for better clarity. Attribute learning and forgetting determine the absolute change $\Delta\mathbf{M}$ in the perception-generating probabilities $\mathbf{G}$ between two "periods" t and $t+1$, i.e. advertising exposures and buying opportunities:

$$\mathbf{G}_{t+1} = \mathbf{G}_t + \Delta\mathbf{M} \tag{2}$$

with:

$$\Delta m_{(b,c),v,t+1} = \begin{cases} (1 - g_{(b,c),v,t}) m_{(b,c),v} & \text{if } m_{(b,c),v} \geq 0 \\ g_{(b,c),v,t}(1 + m_{(b,c),v}) & \text{if } m_{(b,c),v} < 0 \end{cases} \tag{3}$$

In accordance with basic learning theory the gain in attribute learning depends on the amount of brand knowledge already attained. It levels off for product comprehension approaching saturation, while larger gains occur when the association of an attribute with a brand is weak.

The new experience conveyed via advertising leads to a change of the consumers' attitudes toward the brands in the product class. The updated brand positions $\mathbf{D}$ in latent brand space result from two further steps. The first step transforms the advertising-driven probabilities $\mathbf{G}$ into real-valued attribute variables $\mathbf{Z}$:

$$\mathbf{Z} = \log \frac{\mathbf{G}}{1 - \mathbf{G}} \tag{4}$$

which are related to the brand space by the principal components reduction:

$$\mathbf{Z} = \mathbf{AD} \tag{5}$$

where $\mathbf{A}$ is a $V \times R$-matrix of component loadings governing the strength of association between the set of V redundant brand attributes on observational level and the small number of $r = 1, \ldots, R$ directly unobservable brand attitude dimensions ($R \ll V$; the settings are $V = 12$ and $R = 4$). Consumers' fuzzy belief systems are not an issue in this experiment, so the loadings $a_{v,r}$ are either set to 1 for items associated with attitudinal dimension r or 0 for attributes uncorrelated with r. $\mathbf{D}$ is the $R \times (B \times C)$-matrix of positions in brand space; the initial values $d_{r,(b,c),O} \sim N(-2, 4)$ leading to an initial distribution of the $g_{(b,c),v,0}$ strongly biased toward zero and thus producing a sparse brand image profiles matrix $\mathbf{X}$ (see (8) below) in $t = 0$.

In the second step the post-advertising positions then originate from the usual derivation of component scores via:

$$\mathbf{D} = (\mathbf{A}'\mathbf{A})^{-1}\mathbf{A}'\mathbf{Z}' \tag{6}$$

There is also a "technology" side of the ACM. The brand space does not only contain communications-driven but also technology-driven positions manipulated by the firms' product improvement and observable through a set of technical features during actual product usage. The principal components model allows for mapping the technical features into the same space, where discrepancies may be resolved in several ways (technology partly/fully overrules advertising or vice versa). Such a reconciled positions matrix **D** would entail modifications in **Z** via (5). This technology-induced attitudinal change then is propagated into the redundant and fuzzy consumer language via the inverse of (4) viz. the logistic squashing function (7), which squeezes the real-valued attribute values into the interval [0,1]. This technology/advertising aspect is not activated for the current experiment:

$$\mathbf{G} = \frac{\exp(\mathbf{Z}')}{1 + \exp(\mathbf{Z}')} \tag{7}$$

The final step in modeling the latent-space/observable-attributes system introduces a stochastic element into the hitherto deterministic relationships governing (2)-(6). When compared to uniformly distributed random data the probabilities in **G** produce the noisy zero-or-one items of the elongated (brands × consumers) × attributes matrix **X** corresponding to **M** in (1). This is what the marketing agents watch and analyze on the ACM:

$$x_{(b,c),v} = \begin{cases} 1 & \text{if } g_{(b,c),v} > h_{(b,c),v} \\ 0 & \text{if } g_{(b,c),v} \leq h_{(b,c),v} \end{cases} \quad h \sim U[0,1] \tag{8}$$

The unidirectional ideal-point model and the consumer decision rules

Preferences are incorporated into the brand space as ideal points. Ideal-point models face a long tradition (Lehmann, 1971; Ginter and Bass, 1972; Ginter, 1974). They have been used extensively on micro level but also for the analysis of market structure on semi-aggregate ("submarket") level (Cooper and Inoue, 1976). Unlike the conventional ideal-point models the ACM employs a modified "unidirectional" model (see equation (9)). It allows for choice simplification due to irrelevant attitude dimensions and/or satisfaction thresholds. The ACM consumers develop pre-choice and post-choice attitudes towards the competing brands. They form consideration sets of acceptable brands dependent on the expectations aroused by advertising and on their personal preferences. The consumers choose deterministically as long as their decision rule identifies one most attractive alternative. They make random decisions among several brands being equally attractive and therefore indistinguishable in their consideration sets.

The experiment involves several kinds of rationality bounds. Consumers do not strictly optimize. Rather they adhere to a decision style known as "satisficing". They do no longer differentiate among brands once the ideal point of product attributes (compensatory rule) or an aspiration level somewhat lower than the ideal point (non-compensatory rules) has been reached.

Under the modified ideal point model the total attractiveness ("utility") of a product brand b for consumer c is the sum of the utility contributions of the R attitudinal dimensions:

$$u_{b,c} = \sum_{r=1}^{R} \max(0, \min(q_{c,r}, \delta_{b,c,r})) \tag{9}$$

where $\delta_{b,c,r}$ is the consumer's price adjusted attitude (Hauser and Shugan, 1983) toward product brand b represented by its position in the R-dimensional brand space. Price adjustment is done with division by the relative price $p_b/\bar{p}$, where $\bar{p}$ denotes the average selling price of all brands. $q_{c,r}$ is the consumer's current ideal level on the rth attitudinal dimension; for each such dimension zero marks a threshold of relevance that must be exceeded to gain influence in the brand choice. In the "indistinct preferences" scenario the initial $q_{c,r} \sim N(0, 4)$; in the "distinct preferences" setting the q_c are Gaussian with means $(1\ 1\ -1\ -1)$, $(1\ -1\ 1\ -1)$, $(1\ -1\ -1\ 1)$, $(-1\ 1\ 1\ -1)$, $(-1\ 1\ -1\ 1)$, and $(-1\ -1\ 1\ 1)$ for six equal-sized segments with equal $\sigma^2 = 4$.

Brand b is chosen by c if $u_{b,c} = \max(u_{1,c}, u_{2,c}, \ldots u_{B,c})$. If the choice set comprises at least one other alternative of equal attractiveness a random selection takes place. Equation (9) allows for compensation as long as the brand positions do not over-fulfill the consumers' aspirations. Besides that over-fulfillment does no harm. This restriction is one of the elements of bounded rationality fed into the experiment.

For the non-compensatory decision styles two sorts of thresholds are required. For the conjunctive decision rule it is save to assume that the satisfaction levels are fairly lower than the ideal levels. Remember that an attractive brand has to satisfy all these aspired minimum levels. Brand b enters the choice set if it exceeds the minimum bound on all relevant dimensions, i.e.:

$$\sum_{r=1}^{R} \phi(q_{c,r})\phi(\delta_{b,c,r} - \beta_1 q_{c,r}) = \sum_{r=1}^{R} \phi(q_{c,r}) \tag{10}$$

where:

$$\phi(y) = \begin{cases} 1 & \text{if } y > 0 \\ 0 & \text{if } y \leq 0 \end{cases} \quad \text{and} \quad 0 < \beta_1 < 1.$$

For the disjunctive rule brand b enters the consideration set if it fulfills the minimum requirements on at least $r_{\min}$ dimensions, hence:

$$\sum_{r=1}^{R} \phi(q_{c,r})\phi(\delta_{b,c,r} - \beta_2 q_{c,r}) \geq r_{\min}, \quad \beta_1 < \beta_2 < 1. \tag{11}$$

$r_{\min}$ in this experiment is set to one; β_1 and β_2 are set to 0.5 and 0.75.

Half the experimental scenarios foresee non-constant preferences. In this case the consumers adapt their ideal points according to:

$$q_{c,r,t+1} = q_{c,r,t} + \alpha(\delta_{c,r,\max} - q_{c,r,t}), \quad 0 \leq \alpha \leq 1 \tag{12}$$

where α is the adaptation parameter (set to 0.2). $\delta_{c,r,\max}$ is the best value of a brand along dimension r that consumer c has learned about through media advertising (or word-of-mouth; not activated in this experiment).

Note that the preference adaptation is assumed symmetric and the availability of new product knowledge depends on whether consumer c is targeted by brands offering a rich and ambitious attribute profile.

Experimental results

For ease of presenting results the symbols C, V, and D denote the experimental factors choice rule, preference variability and distinctness. P refers to the cumulative profit for the "all profiles" agent (in charge of brand no. 3) and Q to its "profiles chosen" competitor (responsible for brand no. 4). The framework of a simple ANOVA or a multiple regression with dummy variables does not appropriately reflect what has been hypothesized in *H1*. The three market factors are fixed treatment variables. Among the dependent variables the profit results of the mass marketers can be ignored. But there still are two dependent profit variables that may not be mutually independent. Though not part of *H1* or *H2* this must be accounted for in the testing set-up.

A sufficiently general graphical model incorporates all the necessary ingredients: presumably non-homogeneous variances, three binary factors defining eight cells and two possibly correlated profit variables. The concepts and the notation of Edwards (2000) and his MIM3.1 software system (www.hypergraph.dk/) is used here. Starting with the saturated model a first test is for variance homogeneity. This is clearly rejected by Box's test ($p = 0.0035$). Also the assumption of intercorrelated profit variables is dismissed by a likelihood ratio test ($p = 0.068$). Therefore, P and Q are conditionally independent given the market factors. A stepwise backward selection using F-tests then eliminates the edge between D and P and the interaction terms including D ($p = 0.069$; Table I).

Figure 5 shows the resulting graph. This is a block-recursive model where the factors in the first block jointly determine the profit variables in the second block. The accompanying linear interaction terms surviving the backward elimination

Edge excluded	Test statistic	df	p
CP	223.2791	8	0.0000
VP	92.5655	8	0.0000
DP	14.5117	8	0.0694
CQ	84.3393	8	0.0000
VQ	158.5366	8	0.0000
DQ	29.2914	8	0.0003
Removed ... DP			

Table I. Testing a grpahical model for *H1* with backward selection

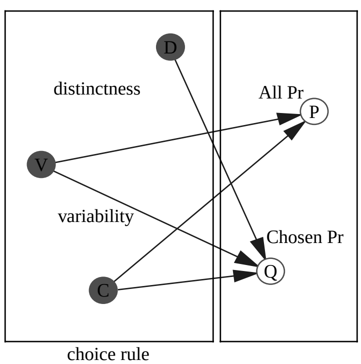

Figure 5. A block-recursive graphical model

are CVP/CDVQ. This means that for "all profiles" there is no significant influence of D and no interaction other than CV influencing P. For "profiles chosen" all the linear interactions involving C, D, and V influencing Q are significant. These findings confirm the set of hypotheses in *H1* for "profiles chosen" and *H1.1a* and *H1.1c* for "all profiles". They lend partial support to *H1.3* regarding the CV interaction for the "all profiles" strategy.

Interpreting Figure 5 it seems plausible that preference distinctness (D) plays a more significant role for the "profiles chosen" agent which relies on the market signals extracted from the initial preference structure. Knowing that $P \perp Q|(C,V,D)$ makes separate regressions for P and Q admissible. These regressions reflect the findings of the graphical model and yield an adjusted R^2 of 0.53 for brand no. 3 and 0.61 for brand no. 4. The variance explained by the market factors is remarkable. One has to bear in mind that the marketing agents' decisions on segmentation and positioning greatly influence the output of a single simulation run. In some runs the agents detect the same product features, sometimes they promote different ones. The size of the target audience as well as the number of claims adopted for the advertising message varies considerably. Since, the experiment focuses on the market factors all these effects are deliberately channeled into the error variance.

To gain a still better understanding of the magnitude of the market factor influence compared to the strategy effect two final regressions are run. These exploratory analyses include strategy as an additional experimental factor with the values "all profiles" = 0 and "profiles chosen" = 1. Cumulative profit then collapses into a single dependent variable. According to Table II strategy (S) interacts strongly with the

Coefficients	Estimate	Standard error	t value	p
Intercept	75,133	2,202	34.125	0.0000
S	25,000	2,655	9.415	0.0000
C	20,621	2,655	7.766	0.0000
V	−22018	2,655	−8.292	0.0000
D	−9040	2,655	−3.404	0.0007
SC	−10275	2,655	−3870	0.0001
SV	−12672	2,655	−4.772	0.0000
SD	−2,793	2,655	−1.025	0.2934
CV	9,050	2,655	3.408	0.0007
CD	5,475	2,655	2.062	0.0398
VC	5,655	2,655	2.130	0.0337
Residual standard error	14,540	on 469 df		
Adjusted R^2	0.5902			
F-statistics	69.99	on 10 and 469 df		0.0000
Without the two-way interactions				
Intercept	76,523	1,565	48.884	0.0000
S	12,130	1,400	8.663	0.0000
C	22,746	1,400	16.246	0.0000
V	−21001	1,400	−14.999	0.0000
D	−4872	1,400	−3.479	0.0005
Residual standard error	15,340	on 475 df		
Adjusted R^2	0.5443			
F-statistics	144	on 4 and 475 df		0.0000

Table II. Multiple regression for the cumulative profit with strategy S as predictor factors C and V. Once the two-way interactions have proved to be significant, it does not make sense to test the individual factor coefficients. But a regression without the two-way interactions induces only small changes in the coefficients for the factors C and V, while S loses half its impact. So, if only main effects are considered the choice rule (C) and preference variability (V) exert an influence on profit almost double as strong as the strategy impact. The strategy factor (S) affects profit largely in conjunction with choice rule and preference variability. The findings are easily extrapolated to real markets. Analysts and managers should pay much more attention to monitoring these psychographics. They may account for differences in sales performance observed between markets or time periods not satisfactorily attributable to variations in strategy.

Testing *H2* is more straightforward as a single dependent variable allows for a more specific model. First a dummy-variables multiple regression is run with the three fixed market factors, their three two-way and one three-way interaction and the difference in relative profit as the dependent variable[1]. No interaction effect appears to be significant. Table III shows the results of a subsequent analysis with main effects only. The residuals are approximate normal. C and V are highly significant ($p < 0.001$); D is not significant thus leading to only a partial confirmation regarding *H2.1a* and *H2.1c* and a rejection of *H2.2-H2.3*.

According to the coefficients in Table III a compensatory decision rule ($C = 1$) reduces the negative difference between brands no. 3 and no. 4 by 5.1 percent and constant preferences ($V = 1$) contribute another 4.4 percent in favor of brand no. 3. This means that the "all profiles" marketing agent benefits from a market scenario where the consumers are well-behaved and more easily predictable. The box-whiskers plot in Figure 6 shows the divergence in the relative profit performance for the two brands. The influence of the choice rule and preference variability is easily recognized while preference distinctness makes no difference. A spectacular R^2 cannot be expected given the close resemblance of the two PBMS strategies. An adjusted R^2 of 0.13 therefore is worth noticing.

The "profiles chosen" strategy for brand no. 4 turns out to be superior irrespective of the market scenario. Figures 7 and 8 show examples of the average trajectories of the revenues for two selected market scenarios. The sales histories over the 12 simulation periods reveal that brand no. 4 becomes particularly successful after the reanalysis and reassessment in period 7. The sales curves also demonstrate that brand no. 3 keeps up with brand no. 4 until $t = 7$ before the reanalysis and strategy revision start boosting the brand no. 4 sales. The most striking example is the "non-compensatory/adaptive and distinct preferences" setting (Figure 7). The smallest gap in revenues occurs for the "compensatory/fixed and indistinct preferences" setting (Figure 8). Apparently, the

Coefficients	Estimate	Standard error	t value	p
Intercept	−9.9784	1.088	−9.174	0.0000
C	5.073	1.088	4.664	0.0000
V	4.390	1.088	4.036	0.0000
D	0.940	1.088	0.864	0.3890
Residual standard error	8.425	on 236 df		
Adjusted R^2	0.13			
F-statistics	12.93	on 3 and 236 df		0.0000

Table III. Multiple regression for the difference in relative profit

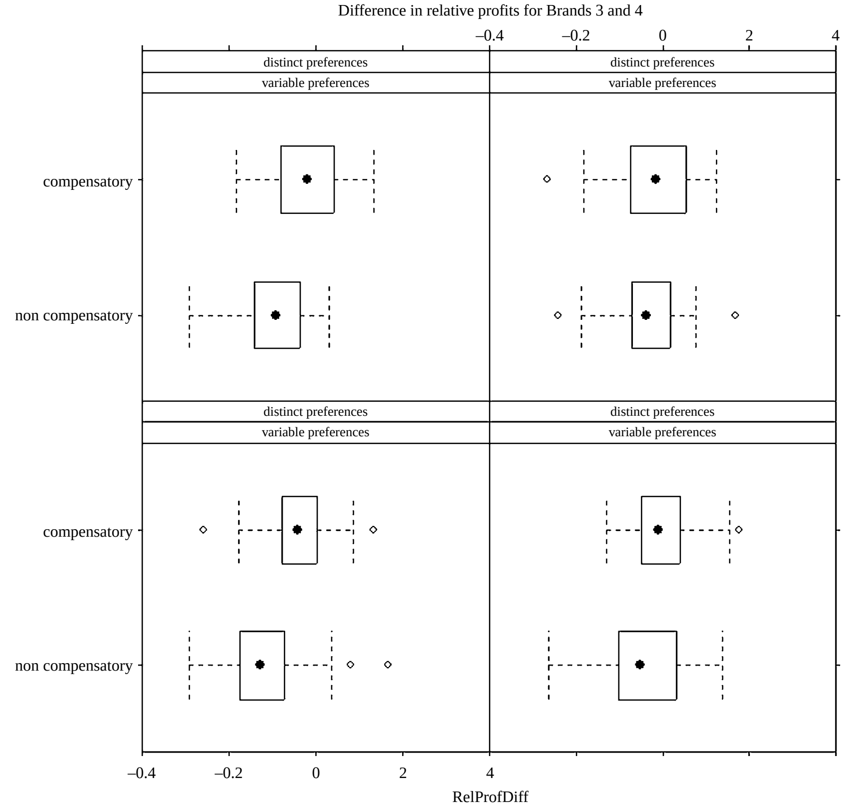

Figure 6.
"All profiles" (brand 3) versus "profiles chosen" (brand 4)

brand no. 3 strategy based on analyzing the larger database of all brand profiles remains competitive as long as the brand images are fuzzy and unstable. Once the consumers' product comprehension permits reliable measurement the "profiles chosen" agent seems to extract more meaningful market structure data than its "all profiles" fellow.

As a collateral finding of the simulation runs one may consider the final configuration of brand positions and consumers' ideal points. Figure 9 shows the $t = 12$ brand space originating from the "compensatory/adaptive and indistinct preferences" scenario. The initial preference distribution (Figure 3) does not indicate any evidence of market segments in a spatial sense. After the marketing agents' partitioning and selective market operation lasting over 12 periods two subregions with fairly separated ideal points and concomitant brand positions have emerged. The ACM is also an instrument for emulating market evolution dependent on the behavioral rules pursued by the firm and consumer agents.

Conclusions and directions for future research

For further developing PBMS analysis and strategy it was important to demonstrate that the "profiles chosen" alternative excels "all profiles" in all market scenarios.

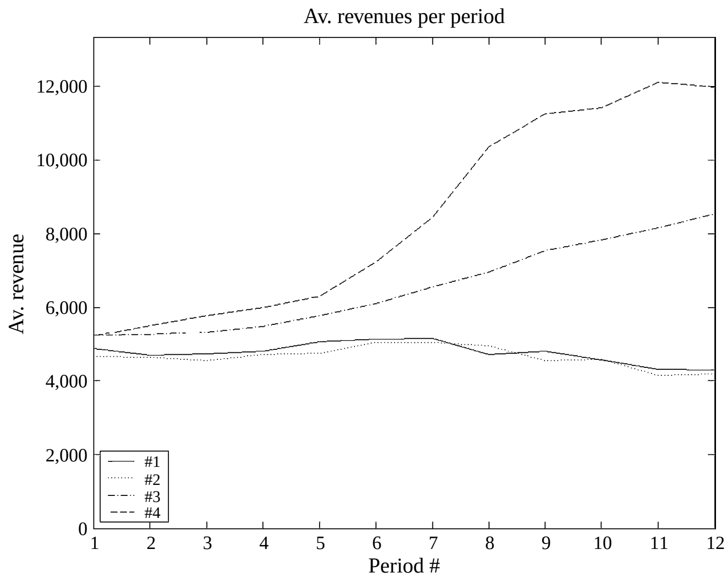

Figure 7.
Revenues earned in the "non-compensatory/ adaptive and distinct preferences" scenario

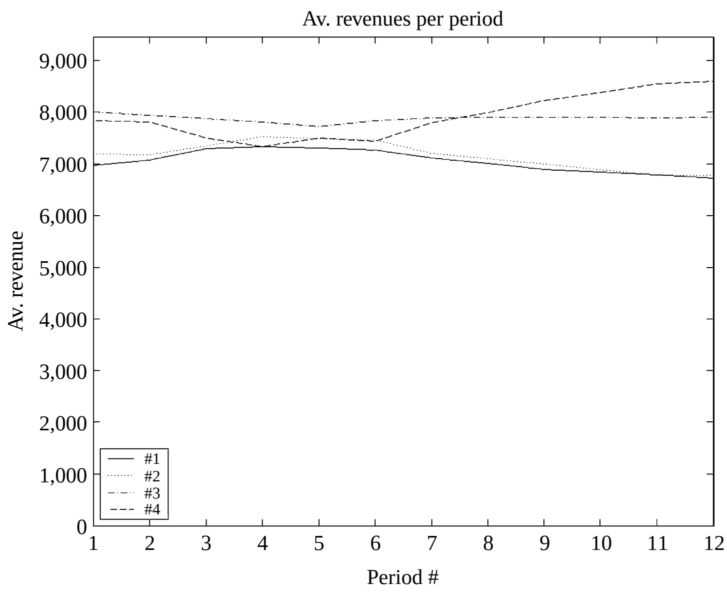

Figure 8.
Revenues earned in the "compensatory/fixed and indistinct preferences" scenario

Given the restricted amount of information processed by the firm agents under the "profiles chosen" strategy one could not expect this clear result.

The ancillary results regarding market factors are illuminating. Marketing model builders have ignored non-compensatory decision rules and time-varying preferences for quite a while. When advanced explanatory models (such as a mixture regression

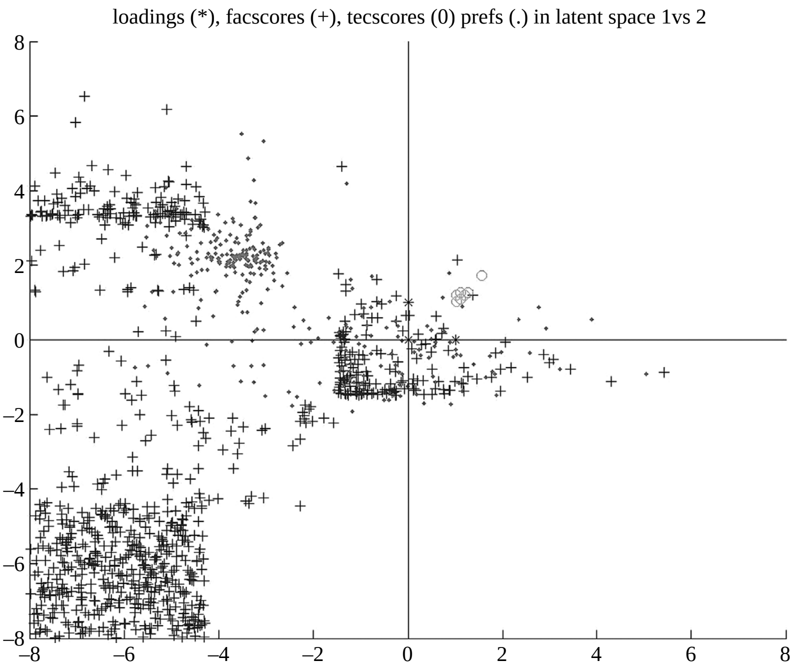

Figure 9.
Perceptions and preferences in $t = 12$ in the "compensatory/adaptive and indistinct preferences" scenario

multinomial logit) are fit to empirical data the measurement results will be published for successful cases and remain unnoticed and invisible for bad fitting ones. Little will be learned about the reasons why a model sometimes achieves a good approximation and sometimes fails to do so. Computer simulation with autonomous agents assists in exploring such reasons. The foregoing analysis demonstrated that elementary market characteristics like consumer choice rule and variability of preferences determine profit performance even for closely related segmentation/positioning strategies. Controlling and monitoring these factors seems to deserve more of the analyst's attention. The small impact of the "preference distinctness" factor is astonishing considering the prominent role of RBMS models. The situation may change if the marketing agents are provided with panel data permitting the application of more advanced response measurement methodology. Note, however, that in real markets comprehensive surveys of brand perceptions are unlikely to occur in short intervals.

Refinements and extensions of this ACM driven experiment may depart in many directions. In particular, the ACM simulations environment (Buchta and Mazanec, 2005) allows for a variety of additional factors unused so far (adaptive reservation prices, brand loyalty, satisfaction, involvement, reactance, word-of-mouth). Also, marketing agents applying some more or less sophisticated analysis and strategy of the response-based type could be enlightening. Another intriguing aspect of simulation experiments is their capability of generating artificial data. Unlike the simulation studies which assume a predetermined probability distribution for producing data the ACM requires nothing else than decision rules for its agents. These rules are grounded in behavioral theory and do not care for assumptions alleviating the life of the analyst.

Note

1. The lm function of the R software system and script language was used (http://cran.r-project.org/).

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Appendix. Outline of the dynamic topology representing network

The DTRN was proposed by Si *et al.* (2000). A simplified explanation of its working principles is elaborated here. Like its non-dynamic counterpart, the TRN, the DTRN encodes a data manifold $\mathbf{X}$ with probability distribution $P(x)$ into a finite set of reference vectors ("prototypes" centroids; typical brand profiles in this application) while respecting the topological properties of the observed data. The quantization techniques which are topologically sensitive are characterized by monitoring the neighborhood structure of their prototypes. This information is stored in an adjacency matrix with zero/one entries and gets updated in each training iteration. Unlike the popular K-means cluster procedure the neighborhood structure in the (D)TRN permits indirect updates of the centroids. In analogy to the fuzzy K-means or overlapping K-centroids clustering (Chaturvedi *et al.*, 1997) this increases the robustness of the quantization results.

The similarity between a data point and a prototype is measured by the Euclidean distance d between the i-th prototype's co-ordinates ("weights") vector $\mathbf{w}_i$ and an input data vector $\mathbf{x}$ with values $x_1,\ldots,x_V$

$$d_i = \|\mathbf{x} - \mathbf{w}_i\| = \left(\sum_{v=1}^{V}(x_v - w_{iv})^2\right)^{\frac{1}{2}} \qquad (\mathrm{A}-1)$$

The TRN and DTRN were inspired by the self-organizing map (Kohonen, 1982, 1988) which employs stochastic approximation ("training") to adapt its weight structure according to the distribution pattern of the input data. Each of the prototypes thus learns to represent a homogeneous subset of data vectors. In the DTRN the number of such prototypes is not predetermined as the training starts with just one prototype equal to an input vector randomly selected from the data set $\mathbf{X}$. Another randomly chosen data point $\mathbf{x}$ is compared to this first prototype $i = 1$ according to (A-1). If d_i fails to drop below the vigilance threshold ρ, the $\mathbf{x}$ becomes a second prototype $\mathbf{w}_g$.

Once there are three or more prototypes they begin to compete with each other such that the winner i^* with:

$$\|\mathbf{x} - \mathbf{w}_{i^*}\| < \|\mathbf{x} - \mathbf{w}_i\|, \quad \forall i, \qquad (A-2)$$

and the co-winner i^{**} with:

$$\|\mathbf{x} - \mathbf{w}_{i^{**}}\| < \|\mathbf{x} - \mathbf{w}_i\|, \quad \forall i \neq i^*, \qquad (A-3)$$

become eligible for a weight update. Before that the winner is subject to the vigilance test. If it fails a new prototype g is introduced and takes the values of the current data point $\mathbf{x}$. The adjacency matrix $\mathbf{S}$ indicating the connectivity among the prototypes is then updated in the following manner:

$$s_{gj} = \begin{cases} 1 & \text{if } j = i^* \\ 0 & \text{else} \end{cases} \qquad (A-4)$$

$$t_{gj} = \begin{cases} 0 & \text{if } j = i^* \\ \infty & \text{else} \end{cases} \qquad (A-5)$$

where t_{gj} is an age counter denoting the number of iterations covered since the creation or last refreshment of the connection s_{gj}.

If the winner i^* passes the vigilance test i^* and all its neighbors get updated by the following "winner-takes-quota" learning rule:

$$\Delta\mathbf{w}_{i^*}(k) = s_{i^*,i}\lambda(k)\frac{\exp\left(-\eta(k)\|\mathbf{x}(k) - \mathbf{w}_{i^*}(k)\|^2\right)}{\sum_{j=1}^{L} s_{i^*,j}\exp\left(-\eta(k)\|\mathbf{x}(k) - \mathbf{w}_{i^*}(k)\|^2\right)}(\mathbf{x}(k) - \mathbf{w}_{i^*}(k)), \quad i = 1,\ldots L \qquad (A-6)$$

where $0 < \lambda(k) < 1$ is the learning rate that decays with the growing number of iterations; $k = 0,1,\ldots$; $\eta(k)$ is an annealing factor that increases during the training.

The last two steps in the DTRN procedure regard updating the connection lifetime record and the removal of superfluous prototypes. Age correction occurs via $t_{i^*,j} = t_{i^*,j} + 1$ and the removal of outdated connections, i.e. setting $s_{i^*,j} = 0$, happens for an age counter exceeding the lifetime limit, i.e. $t_{i^*,j} > \tau$. A prototype i becomes redundant and is abolished if all its connections s_{ij} are zero.

The crucial parameter is the vigilance factor which controls the dynamic creation and demolition of prototypes. Si *et al.* suggest a schedule such as:

$$\lambda = \lambda_0\left(\frac{\lambda_1}{\lambda_0}\right)^{k/k_{\max}} \quad \text{with } \lambda_0 > \lambda_1 \qquad (A-7)$$

and a maximum number of $k_{\max}$ iterations; this makes λ gradually decrease from λ_0 to λ_1. The authors also provide ample evidence of the DTRN performance on synthetic data with known properties and thereby offer advice on choosing meaningful parameter settings.

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