

# Neo-Rawlsian Fringes: A New Approach to Market Segmentation and New Product Development\*

Avi Giloni, Sridhar Seshadri, and Christopher L. Tucci

*Prior research into the link between new product development and market segmentation has focused on two main approaches: (1) design, segment, and do limited competitive evaluation; and (2) segment first, design second. This paper proposes a third approach, which is to simultaneously design, perform segmentation according to benefit and to evaluate against competitive designs. This research uses a benefit segmentation technique based on conjoint analysis (or other techniques that relate product attributes to consumer utility) in which the segments emerge simultaneously with the design based on certain design principles or “strategies.” Herein a method is proposed to narrow down the many possible feasible designs (combinations of attributes) to a finite set and to examine the appeal of each design. Five distinct design strategies are proposed for modeling and studying competitive reaction. These include “traditional” ones such as differentiation and new ones whose fringe customers have high utility. The paper shows that these five strategies are adequate for modeling competitive reaction using simulation. Another contribution of the paper is the way competitive reaction is modeled. In generating and evaluating a design the desire herein is also to assess the defensibility of the design and include it in the evaluation criteria. These issues are addressed by decomposing the solution procedure into two phases. In the first phase, different optimal designs are created based on predefined product development strategies. In the second, these optimal designs are compared against one another with regard to market share and potential to secure market leadership. This work shows that the nature of competition as well as the variability of customer preferences are critical to how a strategy performs. This process uncovers a surprisingly robust design strategy—developing attributes such that a “lower fringe” is most satisfied—that even achieves market dominance under certain conditions. This methodology is also applied to partworth data on refrigerators, which provides a concrete example of the concepts and demonstrates results consistent with the propositions developed earlier in the paper.*

## Introduction

Entry into new markets and incumbent reactions are critically dependent on the product design portfolio choices of firms. Prior research in this general topic area has tended to focus on mechanisms for generating and evaluating product design choices and segmentation possibilities with limited reaction by competitors. Such an approach

Address correspondence to: Christopher L. Tucci, Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland. Tel.: +41 21 693 0023. E-mail: christopher.tucci@epfl.ch.

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designs the product taking into account the existing portfolio of products as well as the resource constraints of the firm (see, e.g., Yano and Dobson, 1998). It is also common to assume in such an approach that competition is static and that any reaction is restricted to price changes. In commenting on the state of the art at the time, Choi and Desarbo (1994 p.451) stated that “despite [a] widely recognized need for analyzing the dynamic effects of competition, few

methodological advances have been published thus far to incorporate formal competitive models.” This paper proposes an approach that starts to address these concerns.

The approach is best explained through an example. Consider the market for a personal digital assistant (PDA). Different attributes for a PDA could be handwriting recognition, weight, battery life, calendar functionality, and price. The traditional method of market segmentation involves collecting data about customer preferences with regard to these attributes using conjoint analysis or other methods (even virtually; see, e.g., Dahan and Hauser, 2002). Conjoint analysis is used to measure partworth functions—that is, the preference for attribute levels. The traditional method continues by identifying segments, for example, by using techniques such as cluster analysis. The design of a PDA follows by tailoring its attributes to a particular segment’s needs. For example, if it were ascertained that students would not pay more than \$99 for a PDA, the firm would choose to design a product for students that is cheaper but weighs more or one that has reduced calendar functionality. The firm, in addition, might consider the price reaction of the competition. Some researchers have also considered the cannibalization of the sales of current portfolio of products in the optimization problem.

This paper deviates from this approach in at least two important respects. The first is the way in which various designs are arrived. A benefit segmentation technique is used that is based on conjoint analysis (or other techniques that relate product attributes to consumer utility) in which the segments emerge simultaneously with the design based on certain design principles or “strategies.” A method is proposed to narrow down the many possible feasible PDAs (combinations of attributes) to a finite set and to examine the appeal of each PDA. For example, if one were to maximize the sum of the utility derived by all clusters of customers, the PDA could be said to appeal “on average” to the clusters. Or, one might choose to design a PDA such that the sum of the utility of top 35% of the users who like the design is maximized (no matter what the rest of the potential market thought of it). In this case, this would be called a design that appeals to the “upper fringe.” Each such PDA thus embodies a product development strategy, such as maximize average utility or maximize the utility of the upper fringe, and therefore yields a potential competitive design. After identifying these potential designs, the resulting products can be evaluated jointly

#### BIOGRAPHICAL SKETCHES

Dr. Avi Giloni is associate professor of operations management and statistics in the Sy Syms School of Business at Yeshiva University. He received his bachelor of arts in mathematics in 1994 from the College of Arts and Science at New York University and his Ph.D. in statistics and operations research in 2000 from the Leonard N. Stern School of Business at New York University. Dr. Giloni has published articles in journals including *Management Science*, *Naval Research Logistics*, *Production and Operations Management Journal*, *Queueing Systems—Theory and Applications*, and *SIAM Journal on Optimization*. His research interests are in optimization, robust forecasting, stochastic system design, and their application to supply chain management.

Dr. Sridhar Seshadri is Toyota Motor Term Professor of information, operations, and management science in the Leonard N. Stern School of Business at New York University. He received his bachelor of technology degree in 1978 from the Indian Institute of Technology in Madras, India, his postgraduate diploma in management in 1980 from the Indian Institute of Management in Ahmedabad, India, and his Ph.D. degree in management science in 1993 from the University of California at Berkeley. He is a fellow of the Institution of Engineers (India). His primary area of expertise is stochastic modeling and optimization. His current research interests are in the areas of risk management for supply chains and performance measurement, optimization, and control of stochastic service systems. He serves as associate editor for *Naval Research Logistics and Management Science* and as senior editor for the *Production and Operations Management Journal*. He is area editor for inventory, reliability, and control for *Operations Research Letters*. He is on the editorial board of the *International Journal of Productivity and Quality Management*.

Dr. Christopher Tucci is professor of management of technology at the Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland, where he holds the Chair in Corporate Strategy & Innovation. He received his Ph.D. in management from the Sloan School of Management at Massachusetts Institute of Technology. His prior work experience was as an industrial computer scientist at Ford Aerospace, where he was involved in developing Internet protocols in the 1980s. Dr. Tucci’s primary area of interest is in technological change and how waves of technological changes affect incumbent firms. He is also studying how the technological changes brought about by the popularization of the Internet affect firms in different industries. He is coauthor of the books *Nurturing Science-Based Ventures* and *Internet Business Models and Strategies* and has published articles in, among others, *Strategic Management Journal*, *Management Science*, *IEEE Transactions on Engineering Management*, *Research Policy*, and *Journal of Product Innovation Management*. In 2004, he was elected to the five-year division leadership track of the Academy of Management’s Technology and Innovation Management Division.

or one on one in a simulation model or using exhaustive enumeration to ascertain their defensibility.

Thus, the second way this research deviates from prior approaches is the way competitive reaction is modeled. In generating and evaluating a design, the desire is also to assess the defensibility of the design and to include it in the evaluation criteria. These issues are addressed by decomposing the solution procedure into two phases. In the first phase, different optimal designs are created based on predefined product development strategies. In the second, these optimal designs are compared with one another with regard to, for example, market share and potential to secure market leadership. Of course, a prerequisite for doing this is to specify the set of product development strategies. Therefore, the space of strategies is an important input to this model.

An obvious product design strategy is to maximize the average utility of all the users of the product. In the PDA example, the objective of such a strategy is to maximize the sum total of utility to all user clusters. But a little thought reveals that there could be alternative strategies. This paper proposes four others that are found to be theoretically interesting. Thus, this paper analyzes the following five strategies: (1) *average strategy*, which maximizes the utility of all the users; (2) *upper fringe (or max-max) strategy*, which maximizes the utility of the users who love the product the most; (3) *lower fringe (or max-min or “neo-Rawlsian”) strategy*, which maximizes the utility of the users who like the product the least; (4) *differentiation strategy*, which increases the utility of the largest percentage of users with respect to a reference product; and (5) *threshold strategy*, which raises the utility of as many users as possible above a “threshold” level. The “segment” such as those that dislike or like a product the most is defined *endogenously* in the proposed approach, thus enabling the simultaneous identification of user segments with product design.

The proposed approach has the following benefits. First, it allows one to question whether a given strategy is defensible to other strategies rather than whether a given product is defensible to other products. For example, pharmaceutical companies lately have pursued a strategy of reducing side effects of blockbuster drugs, and occasionally (e.g., Tagamet and Zantac) they have succeeded. This fast-following side-effect-reducing product may represent a “lower fringe” strategy because the users who like the product the least are happier when the side effects are reduced, even if on average the product is no more

effective than the first-to-market product. Note that, as explained following, the users who dislike the first product the most may or may not be the same users who dislike the second one. It is likely that successful pharmaceutical firms prior to the 1980s did not anticipate an attack from that direction. However, by considering how competitors might enter the fray via a lower fringe strategy, they might have avoided the surprise. Second, this method allows one to explore whether the neo-Rawlsian strategy is robust and what product market conditions would best suit its adoption.

Thus, this paper is an exploration of market segmentation, technological trajectories, attackers’ advantages, and incumbent response using simulation as a method of exploration. It proposes a new way of thinking about product design, competitive evaluation, and segmentation, which under certain circumstances might be more efficient and beneficial. The paper explores the possibility of simultaneity in design and benefit segmentation, taking into account competing designs. Additionally, the results of the simulation demonstrate that segmentation is influenced by how customers are aligned on two different dimensions, namely, agreement on a reference product and how easy it is to change the preference from this product to another product.

This paper also elucidates the concept of product utility as an outlier. In most analysis, the purpose of identifying outliers is to eliminate or ignore them. However, in many cases valuable segments can be carved out of outlier analysis. Incumbents must protect themselves against product strategies aimed at a fringe that captures disaffected customers. Thus, a contribution of this paper is to show that decision criteria such as max-max and max-min should be routinely considered in the product development process.

The paper is organized as follows. The next section briefly reviews the research streams previously mentioned. Then the model is outlined, and results from a simulation analysis of the model and application to real-life data are given. A discussion is then provided of those results and how they relate to the literature. The final section concludes the paper.

## Literature Review

There is a significant amount of literature in the broad area of product design. We concentrate on four topics most relevant to this study: incorporating market

feedback, modeling of price competition, defensive strategies, and research and development (R&D) portfolio selection.

### *Incorporating Market Feedback into Design*

There has been extensive research in product design especially with regard to new product development. One area of research has focused on the use of conjoint analysis to determine market segments and appropriate or optimal product designs. Several papers belong to this category, including Kohli and Krishnamurti (1989); Green and Krieger (1991); Shi, Olafsson, and Chen (2001); and Srinivasan, Lovejoy, and Beach (1997). Green and colleagues have contributed to this literature since the early 1980s. For example, Green and Krieger (1991) described a systematic approach to product design based on conjoint analysis. They suggested developing a cluster based on either buyer background characteristics or partworth preferences and then designing the best product for each segment. They also described several other approaches to designing products. They acknowledged that the model does not provide insight into when competitive reactions might take place and, further, that the use of game theory for making such predictions is in its infancy. Kohli and Krishnamurti (1989) discussed the computational limitations of solving for an optimal product design based on conjoint analysis in the presence of a competitive market. They proposed heuristics for choosing an optimal product design. The way the present research relates to this literature is twofold. Although this modeling framework is not based directly on conjoint analysis, it does directly model customer preferences within the constraints of the maximization problems developed herein. Furthermore, in the section titled “Application to Refrigerator Data,” partworth data from conjoint analysis is directly utilized within the proposed models to explore nonprice (attribute) competitive reactions. Thus, this paper complements the literature on conjoint analysis as it demonstrates its utility for firms that may or may not have already conducted a conjoint analysis.

Others have focused their research on concept testing. Concept testing is the actual testing of various new products or concepts that often can be quite expensive, especially within the pharmaceutical industry. Dahan and Mendelson (2001) studied new product development in the presence of profit distributions

that (possibly) have fat tails. They focused on the problem of determining how many concepts should be tested to maximize expected profit. Their work is related to three existing themes: (1) determining the optimal number of concepts to test where they focus on the testing various “concepts” in parallel; (2) the modeling of product concepts as real options; and (3) the various ways that the actual experimentation may be conducted. Dahan and Mendelson’s contributions are that they provided a new model of parallel concept testing (motivated by previous literature) and that they studied, modeled, and provided managerial insights based on profit uncertainty and focused on the tail (including its shape) of the profit distribution via an extreme event perspective. In contrast, the present research’s focus is one that is strategy driven to determine optimal designs based on various objectives including market share.

### *Price Competition*

Although there has been much research on modeling competition, almost all competitive evaluation has been done through simulation and only for some clusters with just two or three product attributes. The present results are based on a new framework using assumptions that are generally no more restrictive than those found in the literature.

Yano and Dobson (1998) surveyed the literature related to introduction of multiple products with a view to maximize profit. They separated this literature into papers that model customer preferences based on multidimensional scaling and those based on constructing a utility function via conjoint analysis. Regarding competitive positioning, they mentioned that there are several papers in marketing on the problem of introducing a single product to extend a product line. They consider static external competition and cannibalization across the firm’s product and do not consider the cost functions of the firm or competitive reaction (except for price). The papers that incorporate price competition include Choi, DeSarbo, and Harker (1990), Horsky and Nelson (1992), and Choi and DeSarbo (1994). They quoted Robinson (1988) as saying that the most likely short-term reaction to a new product is a change in price. They also suggested that an area of opportunity to extend the product design problems is to incorporate competition. It is noted here that in contrast to the present framework, at best, the models that they survey assume

passive competition; that is, the competitors will not change their product after the introduction of a new product.

Choi and DeSarbo (1994) modeled price competition after a new product was introduced. They extended the model of Choi et al. (1990). Their paper dealt with the case where a new product is introduced and other firms react to it by changing their price. The competitor could behave either strategically or ignore the fact that competitors will adjust price. The analysis is made using a specific conjoint simulator. They noted that “in most conjoint-based procedures, a judgmental set of alternative concept profiles are pre-selected and evaluated using a conjoint simulator” (p. 453). Thus, the manager is assumed to have selected a number of concept profiles to be evaluated against existing brands. Choi and DeSarbo concluded their paper with the result that when a competitor’s price reaction is considered, a superior optimal product profile can be derived. The present methods are applied to their dataset in the section titled “Model Illustrations and Tests.”

### *Defensive Strategies*

Hauser and Shugan’s (1983) paper is one of the few that considered competitive reaction other than price. Within the restrictions described following, they discussed how firms with existing brands should react to a new brand. This is termed *defensive marketing strategy*. They assumed that the defending firm knows the positions of existing products. The defensive actions allowed are price, advertising, distribution, and product improvement expenditures, but they did not consider launch of me-too products. They stated that analysis of equilibrium issues beyond existence of a Nash equilibrium needs use of simulation even for the simple cases studied by Lane (1980). Due to the complexity of their model, they limited analysis to the direction of response. Products are assumed to be positioned in a multiattribute space; each consumer chooses the product that maximizes his or her utility; the utility is a concave function of a summary measure that is linear in the product attributes (which results in a single gradient for a local movement, unlike the present model that permits different gradients); and that awareness and availability can be modeled by advertising and distribution response functions. Regarding product positioning, they suggested that if tastes are segmented and if the competitors clearly outposition the firm’s product in one customer seg-

ment, then a price increase may be optimal. However, if consumer preferences are uniformly distributed, then the defensive strategy should be to decrease price, to improve quality to reinforce the product’s strengths, and to advertise to announce these changes. The present findings regarding the dimensions of benefit segmentation reinforce their conclusions.

Hauser and Gaskin (1984) tested the Hauser and Shugan (1983) defender model as well as the assumption that attributes are measured per dollar and that customers have heterogeneous preferences. Hauser (1988) further elaborated on the concept of defensive marketing strategy. The main assumptions of Hauser’s model are that (1) consumers tastes are uniformly distributed, for a fixed price, (2) brand positions are restricted to a quarter circle, (3) mature brands are in the market and there is no entry or exit, (4) firms have constant returns to scale, and (5) positions are sticky, (i.e., brand positions do not change though firms might move their product positions within this constraint). Hauser’s insights for three firms based on systematic numerical experiments is that if the firms do not anticipate price equilibria, then they tend to position themselves close to one another, whereas when they anticipate price competition they seek maximum differentiation. His results do not extend to the four or five brand case.

### *R&D Portfolio Selection*

Incumbents’ drive in developing new technologies has important implications for the kinds of features that eventually appear in the products and the kinds of attributes associated with the products (Iansiti, 1995; Krishnan, Singh, and Tirupati, 1999; Wheelwright and Clark, 1992). For example, in the rigid hard-drive industry, research into sealing the disk packs led to much higher-capacity disk drives. In the pharmaceutical industry, work on combinatorial chemistry has completely changed the kinds of drugs developed. And in the automobile industry, research in artificial intelligence has led to better and more uniform paint quality in cars. Thus, the choice of technological direction has ultimate ramifications in the form the product will take.

Wheelwright and Clark (1992) discussed the desirability of managing the R&D portfolio through the development of new technologies along two dimensions: (1) how similar the product is; and (2) how similar the process is. They emphasized that mapping the product portfolio is a means to tracking the in-

vestments currently under way and those planned in the future to provide managers with information. Ulrich and Eppinger (2000) proposed four considerations in evaluating and prioritizing R&D projects: (1) competitive strategy (technology leadership, cost leadership, customer focus, imitative); (2) market segmentation (defining the product with respect to a well-known group of customers); (3) technological trajectories (when to adopt or use a basic technology in a product line); and (4) platform planning (which assets to share across products). Scholars (e.g., Desai et al., 2001; Krishnan et al., 1999) noted the interaction between these; specifically, they proposed that even though platform planning could reduce costs, it may constrain the firm's ability to differentiate its product (Desai et al., 2001) or to cover the market (Krishnan et al., 1999). The goal of this mapping is to align the product development process along these four dimensions to ensure a good fit with the company's strategy. Although all four are obviously important, the market segmentation issue with respect to technology and R&D is especially interesting. Also, even though the issue is investigated in the marketing context, it is the least studied of all of them with respect to technology management (Krishnan and Ulrich, 2001, p. 14). Further, Ulrich and Eppinger stated that in performing a market segmentation analysis, "the firm can assess which product opportunities best address weaknesses in its own product line and which exploit weaknesses in the offerings of competitors" (p. 42). The present research takes this one step further by examining the potential response of a competitor as well as the specific segmentation strategies most amenable to sustainable market leadership.

If one looks at the prior research just cited in totality, two interesting implications can be found. The first is that incumbents cannot respond easily to all situations in which competitors or entrants develop new technology. The second is that by designing "defensible" products, firms may be able to take advantage of competitors' relative inertia (or difficulty developing new capabilities) to gain some sustainable advantage in the market. The following section introduces a model of customer preferences and product design so this can be explored further.

## Model

The proposed model is discussed in this section. Many of the assumptions are consistent with those made in

Hauser (1988) and Hauser and Shugan (1983). The components of the model are the design objective, the customer preferences, and technological constraints. These are described next.

### Customer Preferences

The product has  $p$  attributes. The value that attribute  $i$  takes is denoted as  $x_i$ . The design decision is to determine the value  $x_i$  for each of the  $p$  attributes of the product. For example, a PDA can have a keyboard, a screen of a certain size, a weight, and a price. Each of these is an attribute and can take one of several values. It is possible that different combinations of attribute values can be marketed as different grades of the product. However, this research restricts attention to the case when the firm's problem is to design a single product (i.e., to choose a single value for each attribute). It is also assumed that the product cost is restricted to be within a specified range. It is further assumed that each  $x_i$  has a lower bound,  $\ell_i$ , and an upper bound,  $u_i$ , such that

$$\ell_i \leq x_i \leq u_i, \text{ for } i = 1, \dots, p, \quad (1)$$

or, in matrix form,

$$\mathbf{l} \leq \mathbf{x} \leq \mathbf{u}, \quad (2)$$

where  $\mathbf{l} = (\ell_1, \dots, \ell_p)^T$ ,  $\mathbf{u} = (u_1, \dots, u_p)^T$ ,  $\mathbf{x} = (x_1, \dots, x_p)^T$ , and given a matrix  $\mathbf{B}$ ,  $\mathbf{B}^T$  corresponds to the transpose of matrix  $\mathbf{B}$ .

Customers are assumed to fall into  $n$  clusters. Each cluster comprises customers with homogeneous preferences. The fraction of customer population in cluster  $i$  is  $w_i$ . Thus,

$$\sum_{i=1}^n w_i = 1, \quad w_i > 0. \quad (3)$$

Next, a utility function is constructed for each population cluster. Without loss of generality, a reference product is chosen, labeled as A. Let A's  $p$  attribute values be the vector  $\mathbf{a} = (a_j, j = 1, \dots, p)$ . Suppose one is also given a product that has attribute values  $\mathbf{x} = (x_1, x_2, \dots, x_p)$ . Denote the utility derived from this product by a customer in cluster  $i$  by  $u_i(\mathbf{x})$ . The value of  $u_i(\mathbf{x})$  can be expressed as

$$u_i(\mathbf{x}) = u_i(\mathbf{a}) + \sum_{j=1}^p \left[ p_j^i I(x_j \geq a_j) - n_j^i I(x_j < a_j)(x_j - a_j) \right], \quad (4)$$

where  $p_j^i \geq 0$  is the marginal rate of change in utility of a customer in cluster  $i$  for a unit increase in  $a_j$ , and  $n_j^i \geq 0$  is the marginal rate of change in utility of a customer in cluster  $i$  for a unit decrease in  $a_j$ , and the indicator function  $I(\cdot)$  is

$$I(x_j \geq a_j) = \begin{cases} 1 & \text{if } x_j \geq a_j, \\ 0 & \text{otherwise} \end{cases}$$

and

$$I(x_j < a_j) = \begin{cases} 1 & \text{if } x_j < a_j, \\ 0 & \text{otherwise.} \end{cases}$$

Thus, in an extension of prior work, the utility is permitted to change differently for positive and negative changes in a specific attribute. Therefore, given a certain point in the attribute value space, the customers within a cluster may value an increase in the value of attribute  $j$  more (or less) than a decrease; that is, both  $p_j^i \geq n_j^i$  and  $p_j^i \leq n_j^i$  are possible scenarios. Furthermore, it is allowed that customers in cluster  $i$  will not purchase a product unless they derive a utility of at least  $v_i$ . This way, a reservation utility can be modeled for the product.

### Technological Constraints

The firm is assumed to operate under a set of technological, resource, and other constraints. Due to this, not every design represented by (2) is feasible. To model this, a production possibility frontier (PPF) is used to represent the feasible set of design (Hackman and Leachman, 1986; Leachman, 1979), given by

$$\mathbf{F}\mathbf{x} \leq \mathbf{b}, \quad (5)$$

where  $\mathbf{F}$  is an  $m \times n$  matrix and  $\mathbf{b}$  is an  $m \times 1$  vector. Included in this set of  $m$  constraints are budgetary restrictions, as well as technological, capacity, and regulatory constraints.

### Design Objective

As mentioned already, the present work uses five different objective functions to create up to five possible designs (it is possible that different objective functions may occasionally lead to the same design). Before the five strategies under consideration are listed, additional definitions are needed. Let the utility of the  $n$  clusters for a given product with attribute values  $\mathbf{x}$  be  $u_1(\mathbf{x}), \dots, u_n(\mathbf{x})$  or

$$\mathbf{u}(\mathbf{x}) = \begin{pmatrix} u_1(\mathbf{x}) \\ \vdots \\ u_n(\mathbf{x}) \end{pmatrix}$$

Let  $\mathbf{w} = (w_1, \dots, w_n)$ ; that is, the vector of weights or fractions is defined similarly. Let  $[i]$  denote the cluster that derives the  $i$ th lowest utility from the product with attribute values  $\mathbf{x}$ . Thus,

$$u_{[1]}(\mathbf{x}) \leq \dots \leq u_{[n]}(\mathbf{x}). \quad (6)$$

The five objective functions are now developed. Let  $\rho(\mathbf{w}, \mathbf{u}(\mathbf{x}))$  denote the objective function of the firm. The five formulations (product development strategies) are referred to as Maximize the Average Utility, Maximize the Average Utility for the Upper Fringe, Maximize the Average Utility for the Lower Fringe, Differentiation, and Threshold. These are described in detail next.

(i) (*Average Design Strategy*) *Maximize the Average Utility*. The objective function of the firm in this case is to maximize the weighted sum of utilities. Thus,

$$\rho(\mathbf{w}, \mathbf{u}(\mathbf{x})) = \sum_{i=1}^n w_i u_i(\mathbf{x}). \quad (7)$$

(ii) (*Upper Fringe Design Strategy*) *Maximize the Utility for the Upper Fringe*. The objective function is to choose  $(n - h + 1)$  clusters and  $\mathbf{x}$  simultaneously so as to maximize the sum of the highest  $r * 100\%$  utilities where  $r$  is a parameter of the optimization. Thus,

$$\rho(\mathbf{w}, \mathbf{u}(\mathbf{x})) = \sum_{k=h}^n w_{[k]} u_{[k]}(\mathbf{x}), \quad (8)$$

subject to the additional constraints that the sum of the weights of the top  $n - h + 1$  clusters is at least  $r$ , but the sum of the top  $n - h$  weights is less than  $r$ ; that is,

$$\sum_{k=h}^n w_{[k]} \geq r \text{ and } \sum_{k=h+1}^n w_{[k]} < r. \quad (9)$$

(iii) (*Lower Fringe Design Strategy*) *Maximize the Utility for the Lower Fringe*. The objective function is to maximize the sum of the lowest  $r * 100\%$  utilities. Thus, the problem is to choose the  $h$  clusters and  $\mathbf{x}$  to maximize

$$\rho(\mathbf{w}, \mathbf{u}(\mathbf{x})) = \sum_{i=1}^h w_{[i]} u_{[i]}(\mathbf{x}), \quad (10)$$

subject to the additional constraints that

$$\sum_{k=1}^h w_{[k]} \geq r \text{ and } \sum_{k=1}^{h-1} w_{[k]} < r. \quad (11)$$

These constraints are similar to the ones for the Upper Fringe Design Strategy, except that they address the  $h$  lowest clusters rather than the upper clusters.

(iv) (*Differentiation Design Strategy*) *The objective is to design a product that appeals to most customers when it is compared with product A.* Here,

$$\rho(\mathbf{w}, \mathbf{u}(x)) = \sum_{i=1}^n w_i u_i(\mathbf{x}) I\{u_i \geq u(\mathbf{a})\}, \quad (12)$$

where  $I\{x \geq x_0\}$  is the indicator function and thus  $I\{x \geq x_0\} = 1$  if  $x \geq x_0$  and 0 otherwise.

(v) (*Threshold Design Strategy*) *The objective is to maximize the percentage of clusters whose utilities are higher than their threshold values.* Here,

$$\rho(\mathbf{w}, \mathbf{u}(x)) = \sum_{i=1}^n w_i I\{u_i \geq v_i\}. \quad (13)$$

Notice that in (ii) and (iii), the fringe is defined as the  $r * 100\%$  of the population that like a given product the least (lower fringe) or the most (upper fringe). This is in contrast with the use of demographics and psychographics to segment a market.

The problem to be solved can now be formulated as

$$\begin{aligned} \max \quad & \rho(\mathbf{w}, \mathbf{u}(\mathbf{x})) \\ \text{s.t.} \quad & \\ u_i(\mathbf{x}) = & u_i(\mathbf{a}) + \sum_{j=1}^p [p_j^i I(x_j \geq a_j) \\ & + n_j^i I(x_j < a_j)](x_j - a_j) \text{ for all } i \\ \mathbf{F}\mathbf{x} \leq & \mathbf{b} \\ \mathbf{l} \leq \mathbf{x} \leq & \mathbf{u}. \end{aligned}$$

It should be noted that the model does not require the same reference product for all customers. Rather, the model permits a different reference product,  $\mathbf{a}^i$ , for each customer (segment). Thus,  $\mathbf{a}$  can be replaced with  $\mathbf{a}^i$ ,  $a^i$  can be replaced with  $a_j^i$ , and  $p_j^i$  and  $n_j^i$  can be interpreted as the marginal increase or decrease in utility for positive or negative changes in attributes from the reference product,  $\mathbf{a}^i$ .

It is further noted that the proposed approach can be easily extended to the situation where conjoint analysis has already been performed and partworth

information has been collected or estimated. In such a case, it is not necessary to explicitly model a reference product,  $\mathbf{a}$ . Second, all of the potential products that have been utilized in the conjoint analysis should be feasible from the perspective of engineering- or other production-related constraints. Third, the differentiation strategy previously mentioned does not seem relevant since the analysis would no longer be with respect to a particular reference product. In such a case, the remaining four strategies can be employed by a firm utilizing conjoint analysis initially where the firm would want to maximize the following mathematical program. In this program, it is assumed that there are  $K$  attributes, where attribute  $k$  has  $n_k$  levels, and customer (segment)  $i$  gets benefit  $p_{jk}^i$  from level  $j$  of attribute  $k$ . The mathematical program is

$$\begin{aligned} \max \quad & \rho(\mathbf{w}, \mathbf{u}) \\ \text{s.t.} \quad & \\ u_i = & \sum_{k=1}^K \sum_{j=1}^{n_k} p_{jk}^i \text{ for all } i. \end{aligned}$$

## Model Illustration and Tests

### An Illustration

In this section, the model is illustrated using a simple product with two attributes. Then the five product development strategies are analyzed using simulation. A product with three attributes is then further considered, and, finally, the model is applied to real-life data on refrigerators.

Before discussing the details of the experiment, some visualizations of the utility provided by different designs are presented. In the example in Table 1, there are 20 clusters, and the product has two attributes. Each attribute can assume any value between 0 and 10. The reference product is chosen arbitrarily to have attributes  $\mathbf{a} = (7.75, 0.984)$ . The initial utilities of the clusters corresponding to the reference product are shown in column 2. The utility derived by each cluster for four different designs are shown in columns 3 through 6. The four designs are optimal with respect to the Differentiation, the Average Design, the Lower Fringe, and the Upper Fringe design strategies, respectively.

Based on this, a market share is calculated for each of these designs when they compete simultaneously with one another. The present research assumes that customers always buy the product that gives them the



**Table 1. Illustration of Market Share Computation**

Weight ( $w_i$ )	Initial Utility	Differentiation	Average	Lower Fringe	Upper Fringe
0.020	1000.00	1020.64	1018.07	1014.44	<b>1023.07</b>
0.025	990.00	<b>991.00</b>	962.35	955.91	973.35
0.030	975.00	998.69	995.04	990.72	<b>1001.04</b>
0.045	925.00	<b>916.05</b>	888.08	883.27	896.88
0.060	900.00	<b>884.75</b>	847.69	841.81	858.69
0.070	870.00	<b>865.72</b>	841.76	837.14	849.96
0.080	850.00	879.10	878.26	873.76	<b>884.26</b>
0.055	835.00	872.10	889.18	887.43	<b>889.98</b>
0.040	815.00	<b>808.53</b>	790.06	786.97	795.76
0.050	800.00	836.42	<b>858.46</b>	857.90	857.26
0.090	750.00	775.79	786.49	785.02	<b>787.49</b>
0.030	725.00	744.36	751.20	749.83	<b>752.40</b>
0.040	710.00	747.24	<b>771.82</b>	771.69	769.82
0.080	690.00	763.80	817.91	<b>818.85</b>	811.91
0.075	620.00	750.20	854.20	<b>857.73</b>	840.40
0.050	580.00	704.45	803.88	<b>807.25</b>	790.68
0.050	560.00	663.36	740.99	<b>742.71</b>	731.89
0.040	540.00	668.38	773.02	<b>776.96</b>	758.62
0.040	510.00	640.68	745.45	<b>749.08</b>	731.45
0.030	500.00	627.63	733.48	<b>737.79</b>	718.48
Market Share		0.240	0.090	0.365	0.305

most utility, using Lancaster's spatial choice model. Other choice models have been proposed (e.g., Luce, 1959; Tversky and Kahneman, 1992) to model choice behavior. The Lancaster model is appropriate for quantifiable characteristics and horizontally differentiated products (Yano and Dobson, 1998). Our future work will compare the designs for other choice models as well.

For example, the Lower Fringe strategy's design is preferred by clusters 14–20 (numbers in bold in Table 1); the Upper Fringe strategy's design is preferred by clusters 1, 3, 7, 8, 11, and 12; Differentiation strategy's design is preferred by cluster 2, 4, 5, 6, and 9; and the Average strategy's design is preferred by clusters 10 and 13. The market share of a design is obtained by adding up the weights of the clusters that prefer this design over the others. The shares are shown at the bottom of the table. One can similarly calculate the market share for each design when matched up against the other designs in a one-on-one competition. For example, the Lower Fringe is preferred by clusters 14–20 when compared to the Average design, earning it a relative market share of 36.5%. From this illustration one can already appreciate why designing to the lower fringe might sometimes be a good strategy—in contrast, focusing on raising the average utility or on increasing the utility of specific clusters might leave a significant fraction of customers dissatisfied.

### *The Simulation*

A comprehensive simulation study was conducted to compare different design strategies in this section. At the outset, it was observed that if customer preferences were completely homogeneous, then the average design strategy should produce the one design that best satisfies the entire set of customers, rendering competition in product design moot. Therefore, the intent of the experiments was to compare designs under scenarios that have different levels and different types of heterogeneity in customer preferences. Given the novelty of the lower and upper fringe design strategies, most of our attention rests on them in the analysis.

Recall that the parameters of the model were as follows: the number of clusters,  $n$ ; the fraction of customers in cluster  $i$ ,  $w_i$ ; the number of dimensions of the product,  $p$ ; the fraction of customers that constitute a fringe,  $r$ ; the current product,  $A$ ; the initial utility of cluster  $i$  for product  $A$ ,  $u_i(\mathbf{a})$ ; and the magnitude of change in utility for cluster  $i$  with respect to positive and negative changes in dimension  $j$ ,  $p_j^i$ , and  $n_j^i$ . In keeping with the intent of studying the impact of heterogeneity in customer preferences on product design, the decision was made to only vary the weights, initial utilities, and rates of change, that is,  $w_i$ ,  $u_i(\mathbf{a})$ ,  $p_j^i$ , and  $n_j^i$ .

In all the experiments, the number of clusters  $n$  was set equal to 20, which adequately models the potential

**Table 2. Variability of Parameters<sup>a</sup>**

Scenario	Weights	Preferences	Initial Utilities
1	H	H	H
2	L	H	H
3	L	L	H
4	L	L	L
5	H	L	L
6	H	L	H
7	H	H	L
8	L	H	L

<sup>a</sup> H, high. L, low.

heterogeneity of the customers. The size of  $r$  defining the fringe was set to be 0.35. Further, the mean values of the remaining variables were kept fixed at 10 for the  $p_j^i$ 's and the  $n_j^i$ 's and at 1000 for the initial utilities. The scenarios correspond to different levels of variability in the previously provided parameters: The variability in  $w_i$  represents the possibly varying size of customer segments. The variability in both the  $p_j^i$ 's and the  $n_j^i$ 's represents the fact that the customers may appreciate various magnitudes of change in utility for an increase or a decrease in a particular product attribute. The variability in  $u_i(\mathbf{a})$  represents the differing initial utilities of the customer segments for the current product  $A$ . This resulted in the eight scenarios shown in Table 2. Where the table shows “H” the variance is equal to the square of the mean, and where the table shows “L” the variance is equal to one quarter of the square of the mean. This allowed for a study of the effect of variability, in both level and type, of customer preferences on the defensibility of designs.

Although the proposed model is well defined for many product attributes, within the simulation study (in the next section), only two or three product attributes were considered. Indeed, two or three attributes are acceptable for the following reasons. From the mathematical modeling perspective, the major jump in complexity is going from two to multiple dimensions. Just as important, it becomes more difficult to measure the utility of products with many attributes. The problem is that there may be an inverse relationship in product capability and product usability with an increase in the number of attributes. Thompson, Hamilton, and Rust (2005) showed that even though more product attributes are generally looked on favorably by consumers from the perspective of product capability, product usability decreases in the number of product attributes.

When there are two dimensions, the reference product  $A$  was fixed with attributes  $(a_1, a_2) = (1, 3)$ .

The PPF in this case is given by  $a_1^2 + a_2 = 4$ . In the experiments with three dimensions the reference product  $A$  was fixed with design  $(a_1, a_2, a_3) = (1.154, 1.154, 1.156)$  and the PPF was given by  $a_1^2 + a_2^2 + a_3^2 = 4$ . The former PPFs represented a product for which one attribute was relatively more difficult to produce at high levels compared with the other. The second was the PPF for a product whose attributes are equally hard to produce at each given level. The qualitative results did not change appreciably due to these specifications.

To simulate a scenario, values of  $w_i$ ,  $u_i(\mathbf{a})$ ,  $p_j^i$  and  $n_j^i$  for  $i$  equal to 1 to  $n$  and  $j$  equal to 1 to  $p$  were randomly selected. This was accomplished by sampling from a gamma distribution with the appropriate mean and variance called for by the factorial design. Once all parameters were determined, each of the five optimization problems was solved. Each scenario was replicated 1000 times. In the next section, market share was calculated according to both the methods just described.

*Market share for one-on-one competition.* Table 3 shows the market share averaged over all eight scenarios for each design when it competes one on one with other designs for  $p = 2$ . The Average design performs the best on this metric. However, the Lower Fringe design does almost as well. It captures 45.2% of the market share when it competes with the Average and 50.1% when it competes with the Upper Fringe design. Furthermore, when compared with the Differentiation or to the Threshold design, the Lower Fringe design captures approximately 57% and 73% of the market, respectively. The results (not shown) are similar for the three-dimensional case ( $p = 3$ ).

Table 4 shows the average market share for the Lower Fringe design for each of the eight experimental scenarios for the two-dimensional case, and Table 5 shows the three-dimensional case. It can be seen that there is little variation across the scenarios in the market share obtained by the Lower Fringe design strategy when it competes with either the Upper Fringe or the Average design strategy. On the other hand, when competing against the Differentiation or the Threshold design strategy, the Lower Fringe design performs much better in scenarios 3 through 6 in the two-dimensional case. In these scenarios, (see Table 2), the variances of the marginal rates of change in utility (i.e., the variances of  $p_j^i$ 's and the  $n_j^i$ 's,) are low. In fact, in the two-dimensional case the Threshold and the Differentiation designs perform worse in

**Table 3. Average Market Share on a One-on-One Basis<sup>a</sup>**

		Market Share of . . .				
		Average	Upper Fringe	Lower Fringe	Differentiation	Threshold
Against . . .	Average	0.5	0.451	0.452	0.403	0.252
	Upper Fringe	0.549	0.5	0.501	0.434	0.259
	Lower Fringe	0.548	0.499	0.5	0.430	0.262
	Differentiation	0.597	0.566	0.570	0.5	0.377
	Threshold	0.748	0.741	0.738	0.623	0.5

<sup>a</sup>  $p = 2$ .

these four scenarios when competing on a one-on-one basis with the Upper Fringe or the Average design as well. However, in the three-dimensional case, only the Threshold design performs significantly worse in scenarios 3 through 6. Thus,

*Proposition 1: The Lower Fringe strategy is robust to variability in customer preferences. It can result in high market share in a significant number of instances when competing one on one with other product design strategies.*

*Proposition 2: In one-on-one competition, the Threshold strategy is unlikely to capture a large market share when the population is relatively homogeneous.*

*Market Dominance in One-on-One Competition.* Another useful criterion for comparing designs is to tabulate the frequency with which a given design captures more than 50% of the market. This is labeled as “market dominance.” Table 6 shows the frequency of market dominance for the Lower Fringe design strategy for each scenario when  $p = 2$ . It can be seen that the relative performance of the Lower Fringe design vis-à-vis the Average design is better in scenarios

7 and 8 than in the other six scenarios. Referring to Table 2,

*Proposition 3: When competing with the Average strategy, the performance of the Lower Fringe strategy is better when the initial customer utilities are close to one another (low variance) and the marginal rates of change in utility vary considerably.*

This paper now explores whether or not the performance of the Lower Fringe design strategy improves as the variance of the marginal rates of change increase while the variance of the initial customer utilities is unchanged. Figure 1 shows the results of simulations in which the variance of the marginal rates of change is increased systematically while keeping the other parameters unchanged. Each point in this figure corresponds to the fraction of 1000 runs in which the lower fringe strategy achieved greater than 50% market share for that value of variance. The figure clearly demonstrates that the frequency of market dominance increases with increase in the variance of the marginal rates of change of customer preferences. This provides an insight into how the Lower Fringe strategy design becomes competitive: Customers like

**Table 4. Market Share of Lower Fringe Strategy When Competing One on One<sup>a</sup>**

	Average	Upper Fringe	Differentiation	Threshold
Scenario 1	.455	.501	.537	.668
Scenario 2	.457	.506	.523	.666
Scenario 3	.451	.498	.611	.814
Scenario 4	.452	.501	.605	.809
Scenario 5	.442	.496	.623	.809
Scenario 6	.451	.507	.607	.821
Scenario 7	.450	.497	.523	.660
Scenario 8	.458	.504	.531	.653
Average Market Share	.452	.501	.570	.738

<sup>a</sup>  $p = 2$ .**Table 5. Market Share of Lower Fringe Strategy When Competing One on One<sup>a</sup>**

	Average	Upper Fringe	Differentiation	Threshold
Scenario 1	.427	.505	.463	.826
Scenario 2	.432	.506	.463	.819
Scenario 3	.429	.506	.462	.953
Scenario 4	.426	.502	.458	.947
Scenario 5	.422	.504	.471	.943
Scenario 6	.418	.496	.461	.952
Scenario 7	.431	.504	.472	.797
Scenario 8	.430	.503	.457	.799
Average Market Share	.436	.502	.470	.839

<sup>a</sup>  $p = 3$ .

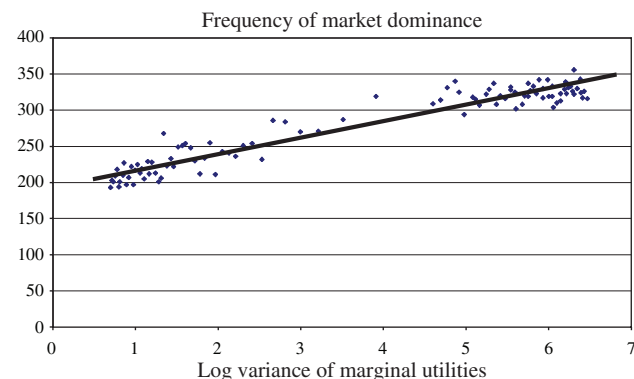
**Table 6. Frequency that Lower Fringe Strategy Has Market Share of at Least 50% in One-on-One Competition<sup>a</sup>**

	Average	Upper Fringe	Differentiation Design	Threshold
Scenario 1	359	518	605	843
Scenario 2	337	529	588	883
Scenario 3	327	519	800	994
Scenario 4	306	516	796	980
Scenario 5	321	494	796	967
Scenario 6	350	540	749	984
Scenario 7	367	493	555	839
Scenario 8	373	528	590	875
Average Market Share	342.5	517.125	684.875	920.625

<sup>a</sup> $p = 2$ .

the initial (reference) product, but there is disagreement among them about how the product can best be improved. When there is higher variance, it is easier to create a direction of improvement that may be overlooked by product designers following other design strategies. This is further discussed in the “Discussion and Conclusion” section.

*Market Share for Simultaneous Competition.* Tables 7 and 8 show the *average* market share of each design when all designs compete simultaneously (i.e., all together) in both the  $p = 2$  and  $p = 3$  cases. It is remarkable that the Average design strategy, which performed quite well in one-on-one competition, performs quite poorly in this test when compared with other strategies. The Lower Fringe design strategy performs relatively well (on the average it captures nearly 22% of the market share where  $p = 2$  and does even better where  $p = 3$  with nearly 27%). However, when  $p = 2$ , the Differentiation design strategy has greater share compared with the Lower Fringe strat-

**Figure 1. Frequency that the Lower Fringe Design Dominates the Average Design for Various Variances of the Marginal Rate of Change****Table 7. Average Market Share in Simultaneous Competition<sup>a</sup>**

	Average	Upper Fringe	Lower Fringe	Differentiation	Threshold
Scenario 1	0.131	0.219	0.211	0.222	0.217
Scenario 2	0.121	0.206	0.193	0.246	0.234
Scenario 3	0.160	0.226	0.225	0.271	0.118
Scenario 4	0.148	0.223	0.222	0.284	0.123
Scenario 5	0.166	0.241	0.225	0.261	0.107
Scenario 6	0.152	0.238	0.236	0.267	0.106
Scenario 7	0.126	0.216	0.203	0.229	0.227
Scenario 8	0.121	0.208	0.205	0.230	0.237
Average Market Share	0.141	0.222	0.215	0.251	0.171

<sup>a</sup> $p = 2$ .

egy in all scenarios; likewise, the Threshold strategy dominates when the variance of  $p_j^i$ 's and the  $n_j^i$ 's are high (Scenarios 1, 2, 7, and 8).

Instead of comparing average share over all replications, the research now compares how often a design wins. To do so, the frequency is tabulated with which each design has the highest, the second highest, and the lowest market share, (Table 9). When  $p = 3$ , the Lower Fringe design stands out as the design that has the highest market share the most often. A more detailed analysis across scenarios reveals that the Threshold design has significantly lower market share in scenarios 3 through 6. Thus,

*Proposition 4: The Lower Fringe strategy is robust across multiple scenarios of customer preferences as well as competition (one on one or all together).*

*Proposition 5: When several design strategies compete in the market, the Threshold design is unlikely to capture a relatively large market share when the population is homogeneous.*

**Table 8. Average Market Share in Simultaneous Competition<sup>a</sup>**

	Average	Upper Fringe	Lower Fringe	Differentiation	Threshold
Scenario 1	0.160	0.257	0.250	0.226	0.107
Scenario 2	0.152	0.244	0.251	0.234	0.120
Scenario 3	0.168	0.282	0.283	0.237	0.030
Scenario 4	0.173	0.279	0.279	0.234	0.035
Scenario 5	0.179	0.277	0.288	0.224	0.031
Scenario 6	0.180	0.286	0.283	0.222	0.029
Scenario 7	0.152	0.251	0.255	0.224	0.119
Scenario 8	0.149	0.254	0.241	0.226	0.130
Average Market Share	0.164	0.266	0.266	0.228	0.075

<sup>a</sup> $p = 3$ .

**Table 9. Frequency of Market Share Rank<sup>a</sup>**

	Average	Upper Fringe	Lower Fringe	Differentiation	Threshold
Lowest Market Share	0.243	0.059	0.0669	0.087	0.544
Fourth Quintile	0.299	0.116	0.115	0.189	0.28
Third Quintile	0.193	0.221	0.210	0.267	0.110
Second Quintile	0.125	0.292	0.293	0.241	0.049
Highest Market Share	0.140	0.312	0.315	0.215	0.018
Average Rank					
1 lowest, 5 highest	2.619	3.683	3.674	3.308	1.716

<sup>a</sup> $p = 3$ .

It is thus observed that the design strategies that perform well in one-on-one competition are not always the best ones to adopt when there are multiple players. In particular,

*Proposition 6: The performance of the Average Strategy is significantly worsened when several design strategies compete in the market compared to one-on-one competition with any of the competing strategies.*

In other experiments not reported here, we investigated whether distinct designs simultaneously superior to all of these five exist. Quite surprisingly, the *best design* in all-together competition either coincided with one of the five or it was within a small distance of at least one of the five in the attribute value space. Further, there seems to be no other apparent systematic method of producing designs that are superior to the five studied here.

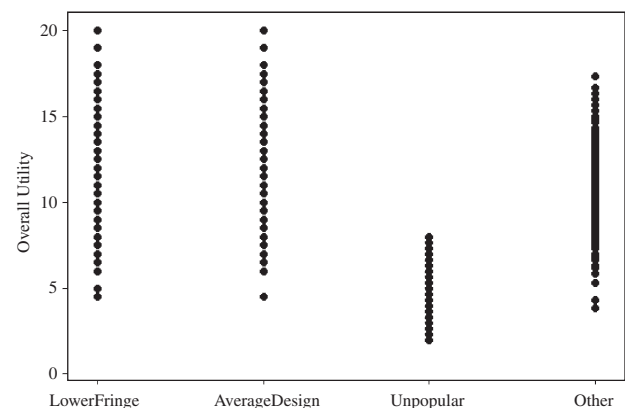
#### Application to Refrigerator Data

This section applies the model to conjoint analysis data on refrigerators from Choi and Desarbo (1994). There are five attributes: (1) Brand name, Capacity, Energy Cost, Compressor Type, and Price. The levels of the various attributes are listed as follows: (1) Brand name: General Electric, Sears/Kenmore, Whirlpool; (2) Capacity (in cubic feet): 22, 21, 20, 19; (3) Energy cost (annual in dollars): 70, 80, 90, 100; (4) Compressor: extremely quiet, somewhat quiet, somewhat noisy, extremely noisy; (5) Price (in dollars): 700, 850, 1000, 1150. The threshold strategy, upper fringe strategy, and average utility strategy all select the optimal product as General Electric, 22 cubic feet, annual energy cost of \$70, Extremely Quiet Compressor, and a price of \$700. On the other hand, the lower fringe strategy selected the same product

except with the brand name Sears/Kenmore. The same results were obtained for fringe sizes from 10% to 35% and for threshold values below 5. When the threshold value is 5 or more, the threshold strategy selects the optimal product to be General Electric, 22 cubic feet, annual energy cost of \$70, Extremely Quiet Compressor, and a price of \$1000. This section describes the case where the fringe value is 30% and the threshold value is 4.

Figure 2 depicts the utility maps of four different designs. Each point in each column represents the utility of at least one customer; thus, each column shows all the unique utilities of the whole population. The first column shows the utilities of all the customer clusters for the design chosen by the lower fringe strategy. The next column shows the utilities for the one design chosen by the other four strategies. The third column shows the utility of a random design, and the fourth column shows the utilities of a suboptimal improvement on the random design. In this dataset, it appears that the population of customers have rather similar preferences (e.g., none of the customer clusters prefers Whirlpool to Sears).

It turns out that when making one-to-one comparisons with the other strategies, the lower fringe strat-

**Figure 2. Utility Maps of Four Different Designs**

egy always provides a slightly lower market share. This is because the design that the other strategies selected (as previously mentioned, they each proposed the same design based on different criteria) is preferred by 144 of the 393 customers, 123 customers are indifferent, and 126 customers prefer the lower fringe design. Thus, in one-to-one comparisons, roughly 52% of the customers prefer the other design, whereas 48% prefer the lower fringe design. However, when making multiple comparisons simultaneously, since there are only two unique optimal designs, the lower fringe strategy obtains the highest market share. Here, it is calculated that the lower fringe strategy is preferred by 40% of the customers whereas the other three strategies each get a share of 20%. The market share of the lower fringe strategy is lower because when the customers are indifferent to all four of the designs (or three of the designs), it is assumed that market share of indifferent customers is shared equally among the designs for which customers are indifferent. It is noted that when the threshold value is 5 or above, the lower fringe strategy selects a design that is superior to the threshold design, and when multiple comparisons are made, the results are similar to those already given in the sense that the lower fringe strategy out performs the others. This illustrates Proposition 6 in that the lower fringe strategy performs better when there are multiple comparisons and also that the average strategy performs poorly in the presence of multiple comparisons. Also, via the lower fringe strategy, one is able to design a new product that is very competitive and can gain a larger market share than one might have thought possible.

## Discussion and Conclusions

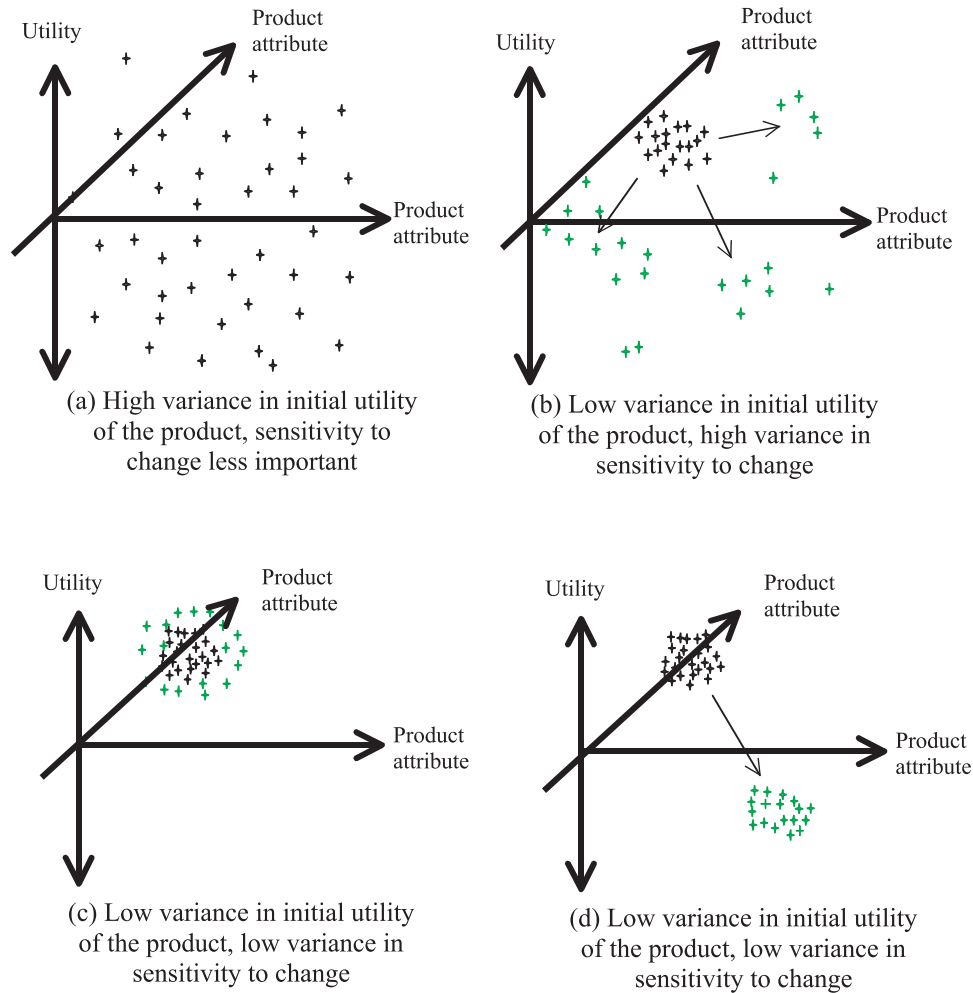
As shown herein, it possible to design a product whose attributes and therefore eventual market segments emerge as a result of analysis of many possible combinations of user preferences. The result of such an analysis provides the ability to compare different design strategies that ordinarily might be overlooked. For example, the Lower Fringe design strategy performs rather well against other design strategies whenever multiple designs compete for market share. What about those markets in which only one other design strategy is used? The present research reveals that the Lower Fringe strategy can outperform even the Average design strategy when two conditions are met: (1) there is high variance across clusters in the rate at

which customer preferences change (i.e., there is wide disagreement among the clusters about changes in the value of the product's attributes); and (2) there is low variance within population clusters with regard to the desirability of the reference product, which for these purposes can be thought of as an incumbent's initial product. These outcomes are depicted for a product with two attributes in Figure 3. The darker + shows the initial value obtained by customer clusters, and the lighter + depicts the subsequent value for each cluster due to the change in design.

The first part of Figure 3 shows no general agreement about the reference product's desirability in the general population, called here "high variance in initial utility, sensitivity to change less important." The reason it does not matter whether the variance in sensitivity to change is high or low is that when the initial utilities are so highly dispersed, further movements, whether large or small, do not affect the dispersion of utilities much. Thus, it becomes very difficult to make much of a market out of a shift in the product's attributes.

The second part of Figure 3 demonstrates a more promising situation. Here the population is not diffuse at all with respect to the reference product, but some consumers are highly sensitive to changes in the product's attributes. In the discussion of Proposition 3, it was demonstrated that under such circumstances, the new product designed to raise the utility of the fringe users who like it the least has the potential to appeal to many users, depending on the dimension on which the new technology improves. What this demonstrates is that the Lower Fringe design strategy does not just win over those consumers who like it the least but also wins over those who happen to be sensitive to design changes, even those who may be relatively pleased with the reference product.

The third and fourth parts of Figure 3 represent situations in which the new product based on the Lower Fringe design strategy is less likely to do well. Even though there is a tight cluster in both (c) and (d), consumers are not very sensitive to changes in the value of product attributes. Observe that variation has two dimensions: the magnitude by which a change can be effected, and the direction in which the change can be made. In (c), the magnitude by which the design changes consumer preferences is small, and, thus, it is difficult to do better than the initial product. In (d), even though the change is substantial, there is not much variation in the direction of change—consumers are highly sensitive to change but in the same direc-

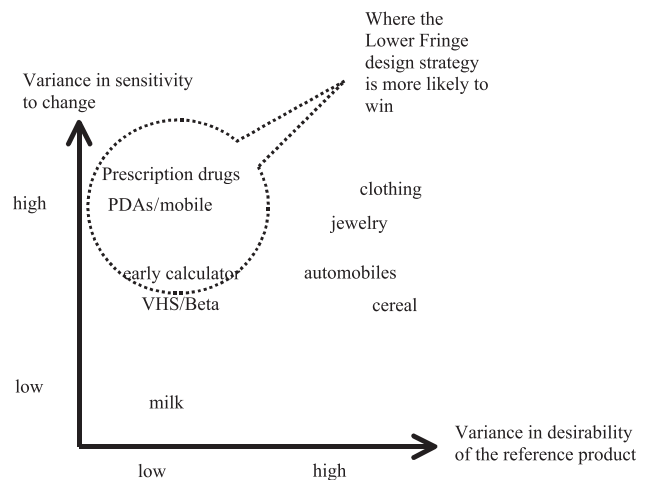


**Figure 3. Schematic: How Consumers Appreciate a Product and Changes to Its Attributes**

tion. In both these cases, designing a product that raises the average utility of all users will out perform a Lower Fringe design strategy almost all of the time. Why? Because by raising the average utility of the users, the new product does not segment the market, but, rather, the entire market migrates to the new product. The Lower Fringe strategy does not quite do as good a job of capturing a large market share in such a scenario.

Figure 4 summarizes the results of the simulation study in markets with two players and vis-à-vis the Average design strategy. Combining the two factors previously outlined, it can be seen that there are four possible combinations: (1) high variance in initial utility and high variance in sensitivity to changing attributes; (2) high variance in initial utility and low variance in sensitivity to changing attributes; (3) low variance in initial utility and high variance in sensitivity to changing attributes; and (4) low variance in initial utility and low variance in sensitivity to chang-

ing attributes. The results suggest that when played one on one against the other design strategies, the Lower Fringe design strategy is likely to come out



**Figure 4. Schematic: Lower Fringe Strategy versus Average Strategy in Different Markets**

ahead when there is low variance in initial utility and high variance in sensitivity to changing attributes. We believe that markets for pharmaceuticals (where reactions to drugs and side effects can create highly different sensitivities to changing attributes), PDAs, cell phones mobile devices (where reactions vary widely depending on Internet access versus e-mail versus wide screens versus the ability to make phone calls), and early calculators (where functions versus weight versus size can be grouped) represent more favorable and defensible markets if employing a lower fringe strategy. Something else in common between these markets is that in addition to being sensitive to change, consumers may change preferences quickly (cf. Bhattacharya, Krishnan, and Mahajan, 1998). Though this issue is not modeled directly in the present paper, this work is complementary to Bhattacharya et al.'s (1998) in that during the process of designing the product and letting the segments emerge, the firm is delaying the definition of the product until some uncertainty about the new market is resolved.

If one assumes that entry into markets based on new technology cannot be instantaneous, then there are four main implications of the study related to the notion of “design for defensibility.” The first is that a Lower Fringe design strategy may mean the firm must develop new technology to serve that fringe. This technology is likely to be different from competitors’ for the very reason that it is designed to serve a different type of group. This leads to the second implication, which has to do with the “resource-based view of the firm.” If the firm is uniquely capable of serving the Lower Fringe relative to competitors, then the firm may find itself in an advantageous competitive position for some time. The third implication is that the Lower Fringe design strategy has more of the element of surprise to it. As asserted already, if it is not the first order of business in many firms’ R&D portfolios, incumbents maybe caught off guard by an entrant’s pursuit of a product with different attributes than anticipated.

One limitation of this study is that the analysis does not explicitly model entry and exit costs. Thus, it is not possible to speak of an equilibrium condition in which different designs could be added or withdrawn from the market either sequentially or simultaneously. Instead, a more limited form of competitive response is being studied in which different designs are introduced into the market simultaneously and then compete head to head in a one-shot game. This sort of

response is, however, one additional step beyond a price response (e.g., a price cut in response to market entry).

The Lower Fringe strategy, though not perhaps the optimal strategy in terms of overall attractiveness to consumers (i.e., performance along the attributes currently valued in the market), may actually be the strategy that can maximize market share. The reason this strategy may be overlooked by incumbents is probably due to the interpretation managers place on designing a better mouse trap. They may feel that it makes more intuitive sense to raise the average utility (make cutting-edge personal computers) rather than the fringe’s utility (a friendlier and more rugged computer). However, raising the fringe’s utility captures not only the fringe itself but also some of the mainstream users who like the alternative attribute developed in the process. Furthermore, when a firm designs a product that satisfies the upper or lower fringe, the design performs quite well in markets where other firms compete on different strategies.

Thus, designing a product whose fringe is happiest may attract customers from all ranges of satisfaction with the incumbent’s initial offering. This research therefore sees the potential importance of not predefining the market segments that matter but rather allowing them to emerge through a process of simultaneous development and regrouping. Of course, design strategies cannot be resolved in isolation. In addition to the manufacturability of a new product and the competitiveness of the new product, firms may consider the ability of competitors to respond to the new product. An analysis of different design strategies as outlined in this paper may allow the firm not only to design something novel but also to keep competitors at bay.

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