ABSTRACT

Title of Dissertation: ESSAYS ON NEW PRODUCT DEVELOPMENT

Lan Luo, Doctor of Philosophy, 2005

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My dissertation comprises three essays that theoretically and empirically

investigate three managerial relevant issues in new product development.

In the first essay, our focus is to develop a methodology that allows

manufacturers to account for the impact of channel acceptance in new product

development. We have developed a model to incorporate the retailer's acceptance

criteria, retailer's product assortment, and competing manufacturers' potential reactions

directly in the design of the new product, thereby maximizing the product's success

probabilities. Our model merges a game-theoretical model with micro-level data on

individual consumer preferences. Therefore, this method provides a rigorous, yet

practical, solution to the problems that manufacturers face regarding channel acceptance.

In the second essay, we examine the impact of subjective characteristics (such as

aesthetics and ergonomics) on consumer's preferences for products. Existing studies of

consumer preferences such as conjoint models are limited in incorporating the influence

of these subjective characteristics into product design. We have developed a model to determine whether the subjective characteristics (such as comfort) are connected with the objective product attributes (such as switch type), and whether both the objective product attributes and the subjective characteristics jointly affect consumer's evaluations towards products. We show that our model outperforms the conjoint model in understanding and designing appealing products for consumers.

In the third essay, our goal is to account for variations in product performance across different usage situations and conditions and to design robust new products. Consumer durables such as appliances and power tools tend to be used in various usage situations and conditions, in which their performance can vary depending on the operating conditions. We apply a Multi-Objective Genetic Algorithm (MOGA) to incorporate multi-function criteria in the generation and comparison of product design alternatives. Our approach will be particularly useful for product development teams that want to obtain customers' buy-in as well as internal buy-in early on in the product development cycle.

We illustrate the approaches described above in the context of a new power tool development project undertaken by a US manufacturer.

ESSAYS ON NEW PRODUCT DEVELOPMENT

By

Lan Luo

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Acknowledgement

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OVERVIEW

Companies operating in today's competitive markets are compelled to develop successful new products in order to ensure the companies' survival and growth. However, the development of new products is also very risky and costly. The high failure rate of new products makes it important for us to explore ways to improve upon existing methodologies in the field of new product development. The development of such methodologies has the potential to save companies millions of dollars in new product development costs. My dissertation belongs to this theme of research in new product development. Figure 1 below provides an overall framework of my dissertation work.

<Insert Figure 1 about here>

In Essay 1, the purpose of our study is to develop a methodology that allows manufacturers to account for the impact of retailers in the new product development process (the right column in the overall framework in Figure 1). In many consumer markets, there is a trend toward the emergence of dominant retailers who account for a significant share of sales in a product category. Examples of such retailers include Home Depot, Wal-Mart, and Toys R Us. In such a channel structure, the dominant retailers' acceptance of the manufacturer's new product often determines the success of the new offering. The purpose of our study is to develop a methodology that allows manufacturers to directly account for the impact of such retailers in the new product development process.

We have developed a model that incorporates the retailer's acceptance criteria, the retailer's product assortment, and the competing manufacturers' potential reactions in wholesale prices directly in the design of the new product. The methodology used in this

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study is as follows. We estimate individual consumer level preferences using a hierarchical Bayesian choice-based conjoint model based on consumer choices among profiles, including "no choice" options. Using game-theoretic methods, we estimate wholesale prices and marginal costs of production for incumbent manufacturers before the entry of the new product. We then develop market scenarios with potential entries of different design alternatives that account for retailer reactions and the subsequent moves of the competing manufacturers. Thus, managers can make the optimal product and pricing decisions with the likely retailer and competitive reactions already factored into the selection process. Our methodology merges a game-theoretic model with micro-level data on individual consumer preferences. Therefore, this method provides a rigorous, yet practical, solution to the problems that manufacturers face regarding channel acceptance at the early stages of product design. We illustrate our approach using data gathered in a new power tool development project undertaken by a US manufacturer.

This essay is under second round review at *Marketing Science*.

In Essay 2, we examine the impact of subjective product characteristics (such as aesthetics and ergonomics) on consumer's preferences for the product (the middle column in the overall framework in Figure 1). In a retail store environment, consumers often evaluate a product based on its overall attractiveness. For example, the users of power tools may evaluate a power tool based on not only its objective product attributes such as brand, price, or switch type but also its subjective characteristics such as whether the tool feels sturdy and easy to use. However, existing studies of consumer preferences such as conjoint models are limited in incorporating the influence of these subjective characteristics into product design and evaluations (Srinivasan, Lovejoy, and Beach

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1997).

In this study, we use customer-ready prototypes to examine whether the consumers use the objective product attributes (such as shape and switch type) as cues to make inferences about the subjective characteristics (such as comfort) of the product, and whether both the objective product attributes and the subjective characteristics jointly affect consumer's evaluations towards products. The proposed model has the form of a Hierarchical Bayesian path analysis model that incorporates the impact of both the objective product attributes and the subjective characteristics on the estimation of individual-level consumer preferences. By incorporating additional information about consumers' ratings for the subjective product characteristics into the estimation procedure, our model is able to provide the designer with better understanding and prediction of consumers' evaluations towards different product design candidates, as compared to a traditional conjoint model.

We illustrate our approach in two studies. The first study was conducted in the context of a new power tool development project undertaken by a US manufacturer. The second study was conducted on toothbrush category to further support the validity and generality of our model.

In Essay 3, our goal is to account for variations in product performance and consumer preferences across different usage situations and conditions (the left and middle columns in the overall framework in Figure 1). In designing consumer durables such as appliances and power tools, it is important to account for variations in product performance across different usage situations and conditions. Since the specific usage of the product and the usage conditions can vary, the resultant variations in product

performance can also impact consumer preferences for the product. Therefore, any new product that is designed should be *robust* to these variations – both in product performances and consumer preferences. By a robust product design we are referring to a design that has (i) the best possible (engineering and market) performance under the worst case variations, and (ii) the least possible sensitivity in its performance under the variations. Achieving these robustness criteria, however, implies consideration of a large number of design criteria across multiple functions. In this paper, our objectives are (1) to provide a method on how variations in product performance and consumer preferences can be incorporated in the generation and comparison of design alternatives, and (2) to apply a Multi-Objective Genetic Algorithm (MOGA) that incorporates multi-function criteria in order to identify good design candidates effectively and efficiently. The generation of design alternatives for prototype consideration will be accomplished using an iterative MOGA, which is used to search for better designs while incorporating the robustness criteria in the selection process. Since the robustness criteria is based on variations in engineering performance as well as consumer preferences, the identified designs are robust and optimal from different functional perspectives, a significant advantage over extant approaches that do not consider robustness issues from multi-function perspectives. We believe our approach is particularly useful for product managers and product development teams, who are charged with developing prototypes. They may find the approach helpful for obtaining customers' buy-in as well as internal buy-in early on in the product development cycle, and thereby reducing the cost and time involved in developing prototypes. We illustrate our approach and its usefulness using a case study application of prototype development for a hand-held power tool.

A previous version of the third essay is published in *Journal of Product Innovation Management* (*Special Issue: Marketing Meets Design,* March 2005) (authored by Lan Luo, P.K. Kannan, Babak Besharati, and Shapour Azarm).

ESSAY 1: NEW PRODUCT DEVELOPMENT UNDER CHANNEL ACCEPTANCE

ABSTRACT

In many consumer markets, there is a trend toward the emergence of dominant retailers who account for a significant share of sales in a product category. Examples of such retailers include Home Depot, Wal-Mart, and Toys R Us. In such a channel structure, the dominant retailers' acceptance of the manufacturer's new product often determines the success of the new offering. The purpose of our study is to develop a methodology that allows manufacturers to directly account for the impact of such retailers in the new product development process.

We have developed a model that incorporates the retailer's acceptance criteria, the retailer's product assortment, and the competing manufacturers' potential reactions in wholesale prices directly in the design of the new product. The methodology used in this study is as follows. We estimate individual consumer level preferences using a hierarchical Bayesian choice-based conjoint model based on consumer choices among profiles, including "no choice" options. Using game-theoretic methods, we estimate wholesale prices and marginal costs of production for incumbent manufacturers before the entry of the new product. We then develop market scenarios with potential entries of different design alternatives that account for retailer reactions and the subsequent moves of the competing manufacturers. Thus, managers can make the optimal product and pricing decisions with the likely retailer and competitive reactions already factored into the selection process. Our methodology merges a game-theoretic model with micro-level data on individual consumer preferences. Therefore, this method provides a rigorous, yet practical, solution to the problems that manufacturers face regarding channel acceptance

at the early stages of product design. We illustrate our approach using data gathered in a new power tool development project undertaken by a US manufacturer.

1. Introduction

Research in the area of new product development abounds in methodologies that focus on the consumer and ways to incorporate their preferences in developing new products (e.g., conjoint analysis). However, given the current state of retailing, focusing on the consumer alone is insufficient.. In industry after industry, a vast consolidation is under way in retailing (see *Business Week*, November 1992; *Financial World*, May 1997; *Advertising Age*, July 2003). With the emerging concentration among retailers, the refusal of a few big-box retailers to carry a new product can effectively block national distribution (*Marketing News*, January 1989). Once viewed as funnels for delivering new products to consumers, retailers now act more as filters. Examples of such retailers include Home Depot, Wal-Mart, and Toys R Us. These big-box retailers tend to be dominant because they are the first place most consumers shop when considering purchasing an item in that product category. Consumers prefer them because of their low prices, attractive assortments and close proximity (*Advertising Age*, July 2003).

Given this trend, the shelf space of these dominant retailers has become the most sought-after real estate among the manufacturers of new products (see "Shelf Space: the Final Frontier", *DSN Retailing Today*, November 11, 2002). At the same time, the scarcity of shelf space is accompanied by the increasing number of new products and line extensions introduced annually (*Advertising Age*, May 1988). Even though consumers may prefer more variety, the limited shelf-space is motivating retailers such as Home Depot to stock relatively few, but fast-moving, items. By adopting such a strategy, these retailers can maximize their category profit by cutting down on inventory costs and the amount of shelf space that they need to devote to a product category (*Marketing News*,

January 1989). As a result, unless manufacturers take this gate-keeping role of their large retailers into account in their product introduction decisions, the retailers may choose not to stock their new products.

Even though retailer acceptance of manufacturer offerings has always been a significant issue in distribution channels (McLaughlin and Rao 1991; Montgomery 1975), its importance has increased in the context of growing retail power (Kadiyali, Chintagunta, and Vilcassim 2000). Recognizing this, manufacturers have been looking for a practical solution to address the problem of channel acceptance early on in the new product development process (see *Wall Street Journal*, November 1988; *Sales and Marketing Management*, March 1996). Several marketing academic researchers have also highlighted the importance of this issue. For example, Corstjens and Corstjens (1995) suggest that "consumer companies might improve their new product success rates if they put more effort in creating retailer value as well as consumer differential advantage". Rao (1997) highlights the issue of channel acceptance in new product development as a topic that deserves investigation. Urban and Hauser (1993) emphasize that the manufacturers should be prepared to include retailer's preferences in their new product introduction decisions, given the increasing power of retailers.

It is surprising that there is, at present, no formal procedure readily available to help manufacturers account for the value they should provide to the dominant retailers. In markets where a retailer plays a dominant role in getting the product/service to the ultimate consumers, it is necessary for the manufacturer of the new product to have a larger view of what constitutes the dominant retailer's category, as well as the potential reactions from competitors and the needs of the end users. The main focus of this study is

to provide such a model so that the manufacturers of new products can increase their chances of a successful market entry. As compared to some traditional strategies (such as slotting allowances or other types of trade promotions) that focus on increasing the attractiveness of product offerings after the new products are designed, our approach focuses on integrating the needs of both the end users and the dominant retailer at the early stages of product design. Therefore, manufacturers can avoid developing new products that do not provide sufficient additional value to the dominant retailer's existing assortment, and they can focus on concepts that are likely to provide value to both retailers and customers.

The rest of this paper is organized as follows. In Section 2, we provide the overview of our methodology and the institutional setting for which it is developed. We also position our work in the context of relevant previous research. In Section 3 we present the details of our methodology. Section 4 describes the empirical application of our methodology. In Section 5 we discuss several model extensions that go beyond the scope of our institutional setting. We conclude in Section 6 with a discussion on the contributions and limitations of our methodology and avenues for future research.

2. Overview of the Methodology

2.1 Institutional Setting and Scope

We first provide an overview of our methodology in the context of the institutional setting for which it is developed with supporting arguments for the scope we have adopted. We consider a focal manufacturer that wants to introduce a new product into a well-defined consumer durable market with one dominant retailer and several competing manufacturers, each currently offering a differentiated product through the

dominant retailer. Our objective is to identify the optimal product that satisfies the needs of both the end users and the dominant retailer, while maximizing the focal manufacturer's profitability.

Our methodology consists of two stages. In the first stage, we estimate individual-level consumer preferences, wholesale prices and marginal costs of the incumbent competitive products before the entry of the new product. In the second stage, using the estimates obtained in stage one, we develop market scenarios to predict the channel acceptance decision for each design alternative. The market scenario is developed based upon the interactions among the retailer, the competing manufacturers, and the manufacturer of the new product in adjusting retail and wholesale prices to maximize their own profits after new product entry. The implementation of such a methodology includes solving a numerical optimization problem for both the retailer and the manufacturers iteratively, given data on individual consumer preferences. The outcome of such iterations is a set of Nash equilibrium retail and wholesale prices. The optimal product and pricing decisions for the focal manufacturer can be mapped out using the estimated equilibrium retail and wholesale prices. We implement this approach using data gathered in the development project of a new hand-held power tool undertaken by a US manufacturer.

We assume that the competing manufacturers react to the entry of the new product by changing only wholesale prices and not any other attribute of the product. Our assumption of "sticky" incumbent product positions is based on the fact that, in our institutional setting, non-price attributes of the incumbent products cannot be adjusted in the short run. In addition, this is a widely adopted assumption in the literature of

competitive product positioning and pricing (Carpenter 1989; Hauser 1988; Horsky and

Nelson 1992; Moorthy 1988). In the long run, the competing manufacturers may decide

to react beyond price. However, it should be noted that, in general, the existence of a pure

strategy equilibrium is not guaranteed when competitive reactions extend beyond price

(see Choi and DeSarbo 1993). There always exists a mixed equilibrium strategy that

allows the manufacturers to choose probability distributions over the non-price product

attributes[1]. Even though this mixed strategy concept provides us with a normative

understanding of the long-term market equilibrium, in reality, the usage of a mixed

strategy in firms is limited because "a firm would not throw a dice on a new product

feature as implied by the mixed strategy" (Choi and DeSarbo 1993). Therefore, we focus

on solving a middle-term problem in which competitive reaction is limited to price.

Despite the general nature of our methodology, we have narrowed our attention to

industries with decentralized channels with no vertical collaboration. We have two

reasons for this. First, vertical collaboration is precluded in practice in the power tool

industry that we focus on. According to our discussion with the marketing executives of

our industrial partner, the practical reason behind this is that, in order to avoid any

commitment on new product acceptance, the retailer would rather not dictate the desired

product positioning to the manufacturers. As a result, the dominant retailer could benefit

from the intense competition in new product entries (on both dimensions of product

positioning and pricing) among the manufacturers. Second, various channel coordination

mechanisms (such as two-part pricing, slotting allowances, and quantity discounts) that

have been discussed in the literature are not a part of the institutional setting of the

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[1] We provide a proof and an illustrative example in Appendix 1.

market for which we develop our model[2]. Our conjecture is that competition between manufacturers in the focal market keeps them from reaching the collusive agreements needed to enforce the coordination mechanisms (Shaffer 1991).

We only explicitly model one dominant retailer in our study. There are three reasons for this. First, market experiences of our industrial partner have indicated that acceptance of the dominant retailer provides the manufacturer of the new product with leverage to convince smaller retailers to accept the item. Therefore, channel acceptance of the dominant retailer, which has approximately 57% of the market share in this product category, is the most crucial for a successful market entry. Second, the second largest retailer in this category carries only store brands (two in number). Therefore, they do not directly compete with the set of national brands the dominant retailer currently stocks. The competitive impact of these products is accounted for in our consumer demand model in the form of "outside goods". Finally, according the market information we obtain from our industrial partner, the second largest retailer is actually not making positive profit in this product category. Therefore, the potential competitive reactions from this retailer are limited[3].

Our methodology contributes to both research and practice dimensions in the following ways. Our research breaks new ground in predictive modeling and scenario analysis by merging a theoretical model with micro data on consumer preferences. Our model differs from existing methods in two important ways. First, we explicitly model

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[2] Empirical evidence of the uniform pricing structure in the power tool industry can be found through publications by Power Tools Institute (PTI), an organization through which member companies obtain aggregate market level data (see www.powetoolinstitute.com).

[3] We note that, in some other categories or industries, it might be necessary to consider the potential reactions from the competing retailers in response to increased assortment of the dominant retailer. We have, therefore, addressed this issue in our section on model extensions (Section 5).

the category management decisions by the retailer so that the retailer's preference is accounted for in the new product introduction decisions, in addition to the needs of the end users. Second, we combine consumer utility models with game theoretic methods to take into account the competitive reactions from the incumbent manufacturers. As a result, the competition is no longer passive. The added realism significantly distinguishes our research from existing research in predictive modeling of new product introductions.

From a managerial perspective, our proposed model provides a theoretically grounded decision support system (DSS) that allows various "what-if" analyses. Furthermore, by focusing on a design strategy that directly incorporates the dominant retailer's interest, this methodology will also provide the manufacturer of the new product with leverage over competitive product offerings in the negotiation process for channel acceptance. Finally, this DSS will be particularly useful for the manufacturers to convince powerful retailers to involve them in the retailers' category management, which will lead to valuable long-term benefits for the manufacturers.

2.2 Relationship to Extant Research

We provide a brief comparison of several related papers with the current study (see Table 1).

< Insert Table 1 about here>

We note that very few studies in marketing have focused specifically on product design for distribution channels. One exception is the study by Villas-Boas (1998), where the author presents a model of product line design for the distribution channel using a game theoretic framework in the context of one manufacturer and one retailer. While

studies of this kind have significant normative value, they assume simple demand functions and channel structures, which limit their value for empirical implementation. In contrast, the focus of this paper is to provide the manufacturers of new products with a rigorous yet practical approach on the issue of new product development under channel acceptance.

As indicated earlier, our model consists of two stages. In stage one, we estimate individual consumer preferences and the marginal cost of production for incumbent products before new product entry. In stage two, the estimates we obtain in stage one are used as inputs to forecast the likely retailer and competitor reactions after the entry of the different design alternatives. Given the optimal retailer decisions and the optimal price reactions of the competing manufacturers to the entry of different design alternatives, the optimal product and pricing decision for the focal manufacturer is chosen. Our estimation procedure *before new product entry* shares some common elements with several papers in New Empirical Industrial Organization (see, for example, Sudhir 2001a; Villas-Boas and Zhao 2005). However, instead of using aggregate-level parameters to specify consumer demand, as commonly used in NEIO, we use a choice-based hierarchical Bayesian conjoint model to obtain individual-level consumer preferences. As consumer heterogeneity is accounted for, we are able to make better predictions about the market shares in any market scenario specified by the researcher, as compared to the aggregate-level estimates (Allenby and Ginter 1995). This is particularly useful in our study since the main focus of our methodology is predictive modeling.

When developing market scenarios *after the entry of the new product*, we assume that the manufacturer of the new product has a finite number of design alternatives and a

market scenario is developed for the entry of each design alternative. The key distinction between our approach and Kadiyali's (1996) work in comparing the pre- and post-entry market structures in the US photographic film industry is that our primary focus is to make market predictions.

In the selection of the optimal product positioning and pricing, the focal manufacturer first predicts the resulting price equilibrium for any possible product position then makes a decision on the positioning of the final product. Such a decision process is quite common in the marketing literature on competitive product positioning and pricing strategies (Carpenter 1989; Hauser 1988; Horsky and Nelson 1992; Moorthy 1988). The rationale behind this process is that, as the key to new product design, positioning decisions are more "sticky" and difficult to make while price decisions are normally market driven.

We denote the market forecast of each possible product position as one market scenario. In each market scenario, we solve for the Nash equilibrium retail and wholesale prices after the introduction of each design alternative. The search for the Nash equilibrium prices involves substituting individual-level conjoint part-worths into the retailer and the manufacturers' profit maximization functions. Therefore, we need to solve a complex numerical optimization problem for both the retailer and the manufacturers simultaneously. We have developed an iterative estimation procedure to solve this game. This iterative procedure is inspired by Horsky and Nelson (1992). We extend their model by introducing individual-level consumer preference estimates and the retailer's profit maximization problem into our framework.

Based on the estimated equilibrium wholesale and retail prices, the manufacturer of the new product can compare the equilibrium retailer category profits before and after the new product is introduced. The design alternative will only be retained if it can increase the category profit for the retailer. This decision rule is similar to the one adopted by Villas-Boas (1998). It has broad support in trade and practitioner journals (see, for example, *Advertising Age*, July 2003), and category management literature (Chen, Hess, Wilcox, and Zhang 1999; Sudhir 2001a).

In sum, we have incorporated individual consumer preferences, competitive reactions to entry, and the acceptance criteria of the retailer into a model of new product development. To our knowledge, our model is the first to provide a formal procedure to help manufacturers taking into account dominant retailers' acceptance criteria in making new product introduction decisions.

3. Methodology Development

3.1 Model Preamble

The market we focus on consists of several oligopolistic competing manufacturers currently selling differentiated products through a dominant retailer with a large market share in the examined product category. The main goal of our model is to help the focal manufacturer to make a successful market entry in such markets.

There are several important characteristics of this market. First, this is a consumer durable market in which several manufacturers and the dominant retailer have an ongoing relationship across many product categories. Second, there are only a few large manufacturers in this oligopoly market. Therefore, both the incumbent manufacturers and the focal manufacturer possess some market power. As a result, the manufacturers have

the ability to set the wholesale prices of their own products. Third, the significant channel power of the dominant retailer implies that the retailer first decides whether or not to carry the product proposed by the manufacturer. If it decides to stock the product, the retailer will set the retail prices of its product line to maximize category profit. This approach is consistent with the actual practice in the examined product category, in which the negotiation between the retailer and the manufacturers over the wholesale prices is absent.

This absence of negotiation can be predicted from the existing literature on channel negotiation and contracting. First, there is an ongoing relationship between the manufacturers and the retailer in this consumer durable market across multiple product categories. In this case, the most effective way of contracting is to limit negotiation in order to minimize transaction costs (Desai, Koenigsberg, and Purohit 2004). In practice, this is particularly true for relatively small categories, such as the hand-held power tool category we study.

Second, the focal category in our study is a mature category in which both the manufacturers and the retailer have good knowledge about the end users' preferences and the specifications of product exchange in the distribution channel. Given this knowledge, the existence of Nash equilibrium profits for both the manufacturers and the retailer will be sufficient to remove any incentive for renegotiation. Hence bargaining ends at the beginning (Iyer and Villas-Boas 2003; Srivastava, Chakravarti, and Rapoport 2000). Intuitively, if the wholesale price charged by the manufacturer is too high, the retailer would choose to sell other manufacturers' product offerings. Meanwhile, if the manufacturer charges a too low wholesale price, it would be leaving money on the table

and it would be better off by increasing its wholesale price. As a result, the manufacturer

will extract the equilibrium payment from the retailer when introducing its product

(Shaffer and Zettelmeyer 2002).

We identify four parties that are involved in this problem: the consumer, the

dominant retailer, incumbent manufacturers with existing products carried by the

dominant retailer, and the manufacturer of the new product. The sequence of our

approach is as follows. First, we estimate individual level consumer preferences and the

marginal costs of production for incumbent products before the entry of the new product

(Section 3.2). Next, we use the obtained estimates to aid the focal manufacturer in the

selection of the optimal product positioning and pricing, with the likely retailer and

competitor reactions already factored into the selection process (Section 3.3).

3.2 Before New Product Entry

Before new product entry, the estimation of the market specifics by the new

product manufacturer is schematically shown in Figure 2. In the following sub-sections,

we will provide detailed explanations of our estimation methods for each block in Figure

2.

<Insert Figure 2 about here>

3.2.1 Individual Level Consumer Preference

We assume that each consumer has an ideal product specification and, for a given

specification, the consumer will always prefer a lower retail price. Prior to new product

entry, the focal manufacturer will collect individual consumer level data using a choice-

based conjoint design and estimate consumer preferences using the hierarchical Bayesian

estimation technique. The details of the consumer demand function are given as follows.

Consider a random utility choice model for a conjoint choice experiment with N individuals and K choice sets with G alternatives each. The utility of individual i for profile g in choice set k is defined as:

$$U_i(\boldsymbol{x}_{gk}, p_{gk}) = \left(\boldsymbol{x}'_{gk}\beta_{ix} + p_{gk}\beta_{ip}\right) + \varepsilon_{igk} \qquad (1)$$

Where $\boldsymbol{x}_{gk}$ = a s×1 vector representing the product attributes of the profile g in choice set k

p_{gk} = retail price of the profile g in choice set k

β_{ix} = a s×1 vector of parameter coefficients weighting product attributes for individual i

β_{ip} = the parameter coefficient of retail price for individual i

ε_{igk} = the random component of the utility

In the utility function specified in equation (1), the retail price is coded as a continuous variable while other product attributes such as brand and switch type are coded as effects-type discrete variables. To allow for outside goods and possible market expansion with the introduction of the new product, we include a "no-choice" option in each choice set as a base alternative (Haaijer, Kamakura, and Wedel 2001)[4].

We assume that, at the population level, individual part-worths have the following multivariate normal distribution:

$$\beta_i \sim Normal(\beta, D) \qquad (2)$$

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[4] Extant literature has discussed the information role of price on buyers' quality judgments of the product (see, for example, Gustafsson, Herrmann, and Huber 2003; Rao and Monroe 1989 and 1996). Expressing the parameter coefficients for non-price product attributes β_{ix} in equation (1) as a linear function of product price, $\beta_{ix} = \alpha_i + \gamma_i * p_{gk}$, we did not find any additional improvement in our model fits, indicating thereby that information role of price on evaluation of non-price attributes is minimal. This is not surprising

Where $\beta_i = (\beta_{ix}, \beta_{ip})$ = a vector of part-worths for the ith individual

β = a vector of means of the distribution of individuals' part-worths

D = a matrix of variances and covariances of the distribution of part-worths across individuals

At the individual level, we assume that the random component (ε_{igk}) follows an extreme value distribution. Hence, the probability of individual i choosing profile g from choice set k can be expressed using the logit expression as follows:

$$\Pr_{igk} = \frac{\exp(x'_{gk}\beta_{ix} + p_{gk}\beta_{ip})}{\sum_{g'=1}^{G}\left[\exp(x'_{g'k}\beta_{ix} + p_{g'k}\beta_{ip})\right] + \exp(a_i)} \tag{3}$$

Where a_i = the constant term representing the utility of the "no-choice" option for individual i.

In the hierarchical Bayesian conjoint model, the parameters to be estimated include the vectors of v_i with $v_i = (\beta_i', a_i)'$ as part-worths and the reservation utility of "no-choice" for each individual, the vector v as the means of the distribution of individual part-worths and reservation utilities, and the matrix D as the variances and covariances of that distribution[5]. The hierarchical Bayesian conjoint model has several advantages over the aggregate choice-based conjoint model (Allenby, Arora, and Ginter 1998; Orme 1998). First, this method captures idiosyncratic preferences occurring at the individual level hence providing more accurate market share predictions. Second, under hierarchical Bayesian methods, the IIA property of the multinomial logit model is

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since customers in this repeat-purchase category are frequent users and have knowledge and experience of product features prior to a purchase.
[5] Details of the estimation procedures are outlined in Appendix 2.

eliminated at the aggregate level, thereby reducing its impact on the market share calculations[6].

In our model, before the introduction of the new product, there are $j=1,\ldots,J$ incumbent competitive products carried by the dominant retailer. We assume that each individual will only purchase one unit of the product at the time of purchase, which is realistic for this category. The market share of product j can be estimated as follows. We use "^" here to represent estimated parameters.

$$m_j = \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_{ij} = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(x_j'\hat{\beta}_{ix} + p_j\hat{\beta}_{ip})}{\sum_{j'=1}^{J}[\exp(x_{j'}'\hat{\beta}_{ix} + p_{j'}\hat{\beta}_{ip})]+\exp(\hat{a}_i)} \quad j=1,\ldots,J \qquad (4)$$

Where N = total number of respondents in the conjoint experiment

3.2.2 Retailer Profit Maximization

We assume that the dominant retailer sets the retail prices to maximize its category profit[7]. Before the introduction of the new product, the retailer's profit maximization can be written as:

$$\max_{p1,p2,\ldots pJ} \pi^r = \left\{\sum_{j=1}^{J}[m_j*(p_j-w_j)*S]\right\}-sc*J \qquad (5)$$

Where π^r = the category profit of the retailer

w_j = the wholesale price of product j

S = market size (in units of potential purchase)

sc = marginal shelf cost (assumed constant)

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[6] The IIA property of the logit model still exists at the individual level in choice-based hierarchical Bayesian models. A random coefficients Multinomial Probit Conjoint model would eliminate this restriction (Haaijer, Wedel, Vriens, and Wansbeek 1998). Given that we were most concerned about heterogeneity across consumers, we did not pursue this refinement.

[7] Empirical evidence of this price-setting rule can be found in Sudhir (2001a) and Villas-Boas and Zhao

We assume that the retailer's pricing decisions are a function of wholesale prices, which are determined by the manufacturers. This assumption of manufacturer Stackelberg price leadership has substantial support from both the channel literature and the NEIO literature (e.g. Betancourt and Gautschi 1998; Shaffer and Zettelmeyer 2002; Sudhir 2001a; Villas-Boas and Zhao 2005). The main justification for this assumption is that, in practice, the retailer is unlikely to make a commitment to carry a product without knowing the product characteristics and the wholesale price commanded by the manufacturer. Only when the proposed product and its wholesale price are acceptable to the retailer, the retailer will proceed to set the retail prices. Therefore, as discussed by Coughlan and Wernerfelt (1989), in an oligopoly market with differential products and a few manufacturers, even when the retailer has substantial market power, the manufacturer still sets wholesale price first and acts as a Stackelberg leader relative to the retailer[8].

Taking the wholesale prices as given, the retailer's first order conditions for equation (5) are:

$$\frac{\partial \pi^r}{\partial p_j} = m_j + \sum_{j'=1}^{J}[(p_{j'} - w_{j'})\frac{\partial m_{j'}}{\partial p_j}] = 0 \qquad j=1,...,J \qquad (6)$$

In equation (6), the retail prices of the existing manufacturers are observable. In addition, we can obtain market share estimates of the incumbent products $(\hat{m}_1, \hat{m}_2,..., \hat{m}_J)$ from the conjoint analysis. Also, given the multinomial logit formation in

---

(2005).
[8] We also estimated the model under two alternative game theoretic model setups – vertical Nash and retailer Stackelberg. Under both model setups the estimates lacked face validity – unusually low wholesale margin and under retailer Stackelberg, unusually high retail margin. In contrast, manufacturer Stackelberg provided good estimates. Details can be obtained from the authors.

equation (4), the derivative of market share (own and across) with respect to retail price can be calculated as follows:

$$\frac{\partial m_j}{\partial p_j} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{ip}\hat{\theta}_{ij}(1-\hat{\theta}_{ij}) \qquad (7)$$

$$\frac{\partial m_j}{\partial p_j{}'} = -\frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{ip}\hat{\theta}_{ij}\hat{\theta}_{ij'} \qquad (8)$$

Where $\hat{\beta}_{ip}$ = the individual parameter coefficient estimate of retail price.

Therefore, we are able to calculate the wholesale prices (w_1, w_2, …, w_J) of the incumbent products based on the expression in equation (6). Hence, the retail category profit before new product entry can be calculated as:

$$\hat{\pi}^{r*} = \sum_{j=1}^{J}[\hat{m}_j * (p_j - \hat{w}_j) * S] - sc * J \qquad (9)$$

3.2.3 Incumbents' Profit Maximization

On the manufacturer side, each incumbent manufacturer chooses its wholesale price to maximize own profit:

$$\max_{w_j} \pi_j^m = (w_j - c_j) * m_j * S - F_j \qquad j=1,...,J \quad (10)$$

Where c_j = the marginal cost of product j

F_j = the fixed cost of product j

The first order conditions for the manufacturers are:

$$\frac{\partial \pi^m}{\partial w_j} = m_j + (w_j - c_j)\sum_{j'=1}^{J}\frac{\partial m_j}{\partial p_{j'}}\frac{\partial p_{j'}}{\partial w_j} = 0 \qquad j=1,...,J \qquad (11)$$

The FOC in equation (11) implies that, when determining the profit maximizing wholesale price, the manufacturer takes into account the influence of its own wholesale

price on all retail prices, which, in turn, affect the market share of each product (Villas-Boas and Zhao 2005).

In addition, as implied in the retailer's first order conditions (i.e. equation (6)), the retailer's pricing responses are a function of the wholesale prices. Therefore, after taking derivatives of the wholesale prices in equation (6) and reorganizing the results, we have the following:

$$
\begin{pmatrix}
\dfrac{\partial p_1}{\partial w_j} \\[2mm]
\dfrac{\partial p_2}{\partial w_j} \\[2mm]
. \\ . \\ . \\[2mm]
\dfrac{\partial p_J}{\partial w_j}
\end{pmatrix}_{J \times 1}
= G^{-1}
\begin{pmatrix}
\dfrac{\partial m_j}{\partial p_1} \\[2mm]
\dfrac{\partial m_j}{\partial p_2} \\[2mm]
. \\ . \\ . \\[2mm]
\dfrac{\partial m_j}{\partial p_J}
\end{pmatrix}_{J \times 1}
\qquad j=1,...,J \qquad (12)
$$

Where $G_{J \times J}$ is a $J \times J$ matrix with the jkth element as:

$$
g_{jk} = \frac{\partial m_j}{\partial p_k} + \frac{\partial m_k}{\partial p_j} + \sum_{j'=1}^{J}[(p_{j'} - w_{j'})\frac{\partial^2 m_{j'}}{\partial p_j \partial p_k}] \quad j=1,...,J \qquad (13)
$$

Substituting above expressions for $\dfrac{\partial p_{j'}}{\partial w_j}$ into equation (11), we can calculate the marginal cost of production for each existing competitive product using the conjoint estimates and the estimated wholesale prices ($\hat{w}_1, \hat{w}_2,..., \hat{w}_J$). The formula is given in equation (14).

$$
c_j = \hat{w}_j + \frac{\hat{m}_j}{\left(\dfrac{\partial \hat{m}_j}{\partial p_1}, \dfrac{\partial \hat{m}_j}{\partial p_2},... \dfrac{\partial \hat{m}_j}{\partial p_J}\right)\hat{G}^{-1}\left(\dfrac{\partial \hat{m}_j}{\partial p_1}, \dfrac{\partial \hat{m}_j}{\partial p_2},... \dfrac{\partial \hat{m}_j}{\partial p_J}\right)'} \qquad j=1,...,J \qquad (14)
$$

To summarize, in Section 3.2.2 and 3.2.3, we have outlined an approach to estimate the wholesale prices and the marginal costs of production for incumbent products *prior* to new product entry. This approach is built upon methods commonly used in the NEIO literature (see, for example, Sudhir 2001a, 2001b; Villas-Boas and Zhao 2005). As we will show, this method of estimating wholesale prices and marginal costs provided estimates with good face validity that generally agreed with the assessments of our client manufacturer. However, other methods of determining marginal costs, such as reverse engineering (Ulrich and Pearson 1998), could also be used to obtain cost estimates in the framework of our model. Similarly, actual wholesale prices could be employed in estimating model parameters if they were available.

3.3 After New Product Entry

The model we presented in equation (1-14) provides estimates of prevailing market conditions before the new product is introduced. This forms the basis for market scenario development and predictions after the entry of various new product alternatives. In Section 3.3.1, we provide an outline of our approach. In Section 3.3.2, the detail of our estimation algorithm is presented.

3.3.1 Outline of Our Approach

The manufacturer has a finite set of design alternatives for the new product. These design alternatives are constructed by enumerating all the possible combinations of attribute levels defined in the conjoint analysis. Based on the product specification, we assume that the focal manufacturer can approximate the marginal cost for each alternative. When the focal manufacturer makes an attempted product entry, its goal is to select a product specification and a wholesale price that: (1) will be accepted by the

dominant retailer in the distribution channel and (2) is most profitable as compared to other design alternatives which are acceptable to the retailer. In meeting this objective, the manufacturer takes into consideration: (1) the locations of the existing products; (2) individual consumers' response to new product entry; (3) the manufacturers of the existing products changing their own wholesale prices as a competitive move; and (4) the retailer making adjustment in retail prices for the revised product line. An outline of our approach is presented in Figure 3.

<Insert Figure 3 about here>

In order to select the optimal product with all the above considerations, we evaluate all the design alternatives for the focal manufacturer. With a finite set of design alternatives, a market scenario is developed to solve for the Nash equilibrium wholesale and retail prices after the entry of each alternative. The search for the Nash equilibrium wholesale and retail prices involves solving the retailer and the manufacturers' profit maximization functions simultaneously. As described in Figure 3, our estimation procedure is composed of iterative interactions between the retailer, the competing manufacturers and the manufacturer of the new product in adjusting the retail and wholesale prices in response to the new product entry. This iterative procedure is an extension of the procedure adopted by Horsky and Nelson (1992). The focus of our approach is not the process of these interactions, but the new equilibrium outcome. This new equilibrium outcome is predicted for each design alternative and the optimal new product is selected accordingly. The detail of our estimation procedure is given as follows.

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Given an initial wholesale price of the new product alternative and current wholesale prices of the existing products, the retailer first chooses the retail price for the new product and adjusts the retail prices of existing products to maximize its category profit. The retailer's profit maximization follows the expression in equation (15). We use "tilde" here to highlight the variables that are affected by the introduction of the new product alternative.

$$\max_{\tilde{p}_1, \tilde{p}_2, \ldots \tilde{p}_J, \tilde{p}_{new}} \tilde{\pi}^r = \left\{ \left(\sum_{j=1}^{J} [\tilde{m}_j * (\tilde{p}_j - \tilde{w}_j)] \right) + \tilde{m}_{new} * (\tilde{p}_{new} - \tilde{w}_{new}) \right\} * S - sc * (J+1) \quad (15)$$

As we can see, with the addition of the new product, the retailer may be able to provide a better match between its product assortment and the heterogeneous consumer preferences. As a result, the market share of "outside goods" may shrink and the retailer could enjoy additional category profit. However, this is only true when the new product could satisfy some unmet consumer demand, which will be reflected in the market share estimates of the new product and the incumbent products. Otherwise, the new product alternative would be considered as unfavorable and the retailer could decline to carry the product.

The first order conditions for equation (15) are:

$$\frac{\partial \tilde{\pi}^r}{\partial \tilde{p}_j} = \tilde{m}_j + \sum_{j'=1}^{J+1} [(\tilde{p}_{j'} - \tilde{w}_{j'}) \frac{\partial \tilde{m}_{j'}}{\partial \tilde{p}_j}] = 0 \qquad j=1, \ldots, J+1 \quad (16)$$

In order to solve the optimal retail prices using retailer's first order conditions, we substitute the expressions for the market shares and the expressions for $\frac{\partial \tilde{m}_j}{\partial \tilde{p}_j}$ and $\frac{\partial \tilde{m}_{j'}}{\partial \tilde{p}_j}$ into equation (16) using formulations from the conjoint model (refer to formulae in equations (4), (7), and (8)). Because the individual-level conjoint part-worths obtained from the

hierarchical Bayesian conjoint model are embedded in these expressions, heterogeneous consumer preferences are accounted for when solving the optimal retail prices.

Given this set of new retail prices $(\widetilde{p}_1, \widetilde{p}_2, ..., \widetilde{p}_J, \widetilde{p}_{new})$, all the manufacturers (including the incumbent manufacturers and the manufacturer of the new product) then adjust their wholesale prices to maximize own profits. The manufacturers' profit maximization problem is similar to the one described in equation (10). And the adjusted wholesale prices can be calculated in a similar fashion as described in the previous paragraph, using the following FOCs for the manufacturers:

$$(\widetilde{w}_j - c_j) + \frac{\widetilde{m}_j}{\left(\dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_1}, \dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_2}, ... \dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_{J+1}} \right) \widetilde{G}^{-1} \left(\dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_1}, \dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_2}, ... \dfrac{\partial \widetilde{m}_j}{\partial \widetilde{p}_{J+1}} \right)'} = 0 \qquad j=1,...,J+1 \qquad (17)$$

Where $\widetilde{G}_{(J+1)x(J+1)}$ is a *(J+1)x(J+1)* matrix with the *jk*th element similar to the expression in equation (13).

Next, the retailer re-adjusts the retail prices given the adjusted wholesale prices. And the manufacturers re-adjust the wholesale prices based on the adjusted retail prices. This cycling process continues until the generated prices converge. The converged prices represent the Nash equilibrium prices after the entry of the design alternative.

We develop a market scenario for the entry of each design alternative. Based on the equilibrium wholesale and retailer prices, we calculate the equilibrium category profit for the retailer after including the new product alternative into its assortment. If this profit is an increase over current profit, then the design alternative is retained for further consideration. If not, it is eliminated. Among the retained design alternatives, the optimal new product is the one that maximizes the focal manufacturer's profit.

3.3.2 Iterative Algorithm

The estimation procedure for solving the profit-maximizing retail prices (second block in Figure 3) and the profit-maximizing wholesale prices (third block in Figure 3) involves the use of an iterative algorithm. In this section, we provide a brief description of the algorithm.

We start with solving profit-maximizing retail prices (second block in Figure 3). Let $\tilde{p}$ denote the vector of retail prices to be solved. Let g denote the gradient at $\tilde{p}$

(i.e. $g = \dfrac{\partial \tilde{\pi}^r}{\partial \tilde{p}}$). The iterative process can be described as follows:

Step 1: Choose the starting value of retail prices as $\tilde{p}_0$.

Step 2: Repeat the following until the convergence criterion is satisfied:

(a) Start with step size $\lambda = 1$.

(b) Let $\tilde{p}_{t+1} = \tilde{p}_t + \lambda g_t$. If retailer category profit evaluated at $\tilde{p}_{t+1}$ is greater than retailer category profit evaluated at $\tilde{p}_t$ (i.e. $\tilde{\pi}^r\big|_{\tilde{p}_{t+1}} > \tilde{\pi}^r\big|_{\tilde{p}_t}$), move to $\tilde{p}_{t+1}$ and go to step (c). Otherwise, reduce the step size λ to $\dfrac{1}{2}, \dfrac{1}{4}$, and so on, until an improvement in the retailer category profit results. If the limit of "squeezing" the step size is reached before an improvement in retailer category profit is found, go to step 1.

(c) Check the convergence criterion. If not satisfied, go to step (a).

The algorithm of solving the profit-maximizing wholesale prices (third block in Figure 3) is similar to the algorithm described above. After choosing a set of starting values, we first solve for the optimal wholesale price for manufacturer 1 using line

search, given the current wholesale prices of manufacturer 2 through $J+1$. Next, we solve for the optimal wholesale price for manufacturer 2 through $J+1$, each time incorporating any price changes made in earlier iterations. Then, we start over from manufacturer 1, manufacturer 2, and so on. This cycling procedure continues until the generated wholesale prices converge.

In short, our estimation procedure of solving for the Nash equilibrium prices includes the inclusive elements of solving for the retailer profit maximization problem (second block in Figure 3) and solving for the manufacturer profit maximization problem (third block in Figure 3) iteratively.

This algorithm is similar in spirit to Steepest Ascent Gradient method with line search. It has been proved to be an effective method for numerical maximization when the starting values can be efficiently identified and the search is in a sufficiently small neighborhood (Goldfeld and Quandt 1972; Greene 2000; Train 2002). In our model, at the beginning of the iteration process, we use the actual retail prices of the existing products before new product entry as the starting values of retail prices for incumbent products, and the marginal cost plus average wholesale margin plus average retail margin is used as the starting value for the retail price of the new design alternative. After the iteration starts between the second block and third block in Figure 3, we use the prices calculated from the previous iteration as the starting values. These starting values appear to work very well in the estimation procedure. In addition, we can effectively define the boundary of the search region because the nature of our problem determines that the adjusted retail prices cannot be lower than wholesale prices and the adjusted wholesale prices have to be in between the retail prices and the marginal costs. Both aspects have

made the estimation procedure of Steepest Ascent work very efficiently in our estimation problem.

A drawback of using iterative gradient methods is that the maximum obtained may be a local maximum rather than global maximum (Goldfeld and Quandt 1972; Greene 2000; Train 2002). In the context of this study, this issue concerns two optimization problems: the retailer's profit maximization problem and the manufacturers' profit maximization problem. Regarding the latter, we are able to analytically show that there exists a price equilibrium among the oligopolistic manufacturers (see detail of our proof in Appendix 3).

With respect to the retailer's profit maximization, the global concavity of a logit-based profit function needs to be determined on a case by case basis (see Hanson and Martin 1996; Schmalensee and Thisse 1988). However, numerically proving that a function is concave is extremely difficult because the Hessian matrix must be evaluated over the entire function domain. Therefore, we have adopted several heuristic methods to examine the shape of the retailer's profit function. First, we observed the three dimensional plots for the retailer's profit maximization problem with two manufacturers. The objective function appeared to be globally concave over the specified search region. Second, we examined the Hessian matrix with all possible combinations of integer price levels over the search domain and found all of the computed Hessians to be negative semi-definite. Finally, we used different starting values for retail prices for several market scenarios and obtained highly similar estimates of the profit maximizing prices. We recognize that the retailer's profit function may not be concave for a different application. In that case, our gradient search method can be combined with Hanson and

Martin's (1996) procedure to find a path of prices to recover the global optimum, even when the shape of the objective function is not concave.

In using our algorithm, we adopt an exhaustive enumeration over the product attribute space to find the optimal new product alternative. In our application with a sample size of 249 respondents in the conjoint experiment, the computation time for each market scenario ranges from 30 minutes to an hour on a Pentium 4 personal computer. The implementation of this methodology was completed within 27 hours for a design set of 36 alternatives. Therefore, we believe that exhaustive search will be applicable to most of the conjoint-based product design projects, because a typical conjoint experiment involves six or fewer attributes (including brand, price, and four or fewer attributes of product features) with five or fewer levels per attribute. Anything beyond this would overburden respondents and lead to unreliable responses (*Sawtooth CBC Users Manual*, Chapter 3). However, when we do have a large problem with as many as 625 (5x5x5x5) possible combination of product features, we may need to decrease the number of alternatives considered by first evaluating the conjoint part-worths across respondents and eliminating the attribute levels that are less preferred and cost more to produce.

<u>4. Empirical Application</u>

4.1 Consumer Preference Estimation

We applied the proposed model using data collected in a development project of a new hand-held power tool undertaken by a US manufacturer. Working as a team with our industrial partner, we identified an initial set of fifteen product attributes. Next, we conducted some exploratory research to narrow down the set of product attributes to six as they were considered as the most critical by the end users. These six product attributes

are: brand, price, power rating, life of product, switch type, and actuator type. Four different brands were considered, along with three levels of price, three levels of power rating and three levels of life of product. The switch attribute consisted of four levels. And there were two types of power actuators (A and B). Using orthogonality as the design optimality criterion (Addelman 1962), we constructed 16 choice scenarios. Each choice occasion included two alternative designs and a "no-choice" option with verbal descriptions indicating the levels of product attributes. And 2 additional choice scenarios were constructed for validation purpose.

We obtained conjoint data from 249 participants. Participants for this study include metal workers and construction workers (who make up 80% of the user base for the tool) recruited from job sites and construction sites across the US market. A pre-experiment screen was done to ensure that all of our participants are regular shoppers of the dominant retailer in the examined product category. This retailer has approximate 57% of the market share for the distribution of this product category. The data were collected, coded and analyzed using the Sawtooth Software. We estimated the vector of conjoint part-worths for each individual in our sample using the hierarchical Bayesian conjoint model.

Since we assume the consumer will always prefer a lower retail price for a given specification, the retail price is coded as a continuous variable while the other product attributes such as brand and switch type are coded as effects-type discrete variables. The first 5,000 iterations were used as burn-in. To assess convergence, we monitored the on-screen display of the point estimates of the population mean calculated from each iteration. We also halted and restarted the computation several times and compared the

estimates arising from different stages of the computation progresses. The next 10,000

iterations were used to obtain the posterior estimates. A skip factor of 10 was chosen to

compensate for the fact that successive draws of the posterior estimates may not be

independent. Therefore, 1,000 draws were used to construct the part-worths for each

respondent in the sample.

Table 2 gives the estimates of the conjoint part-worths for 5 randomly selected

respondents in our sample. As we can see, there exists a noticeable heterogeneity in

preferences among the respondents. For example, even though Subject 58 and Subject 97

prefer an amp rating of 12, it is considered the worst amp rating level for Subject 123.

Similarly, top slider switch is Subject 3 and Subject 123's favorite switch while it is also

the least preferred switch for Subject 58. Therefore, it is important to consider individual-

level consumer preferences when making predictions of market shares under different

market scenarios.

<center><Insert Table 2 about here></center>

Table 2 also gives the posterior standard deviation of each estimate, the log-

likelihood value of estimated model, the chi-square value, and the Pseudo R^2 value. All

fitness statistics indicate that the estimated model provides reasonable goodness of fit to

the data. The results from our 2 holdout choice scenarios are given in Table 3, which also

indicate a good fit of our model.

<center>< Insert Table 3 about here></center>

The estimates we obtained here are used to estimate the market specifics before the

entry of the new product and to predict the changes in market shares with the introduction of

the new product alternative.

4.2 Market Specifics before New Product Entry

Before the entry of the new product, the dominant retailer in our study carries 3 products in the product category. The specifications of these 3 competitive products are given in Table 4.

<div align="center"><Insert Table 4 about here></div>

Based on the product specifications in Table 4, we estimated the market shares of the incumbent products using equation (4) presented in the methodology section. Our estimation results suggest that 24.90% of the consumers in our sample will not purchase any of the existing products currently carried by the dominant retailer, which indicates a good opportunity for market expansion with the entry of the new product (see Table 5). To assess the face validity of our model, we compared the estimated market shares after the percentage of "no-choice" is factored out with what our industrial partner knows as the market shares of these products (we call them as the "observed market shares"). These market share data were obtained from Power Tool Institute (PTI), an organization that provides its member companies with market level data such as the sales of the major power tool manufacturers and market sizes of different power tool products. Our industrial partner is a member company of PTI hence has access to the market share data. As Table 5 shows, the estimated market shares from our conjoint experiment are reasonably in line with the observed market share values.

<div align="center"><Insert Table 5 about here></div>

From Tables 4 and 5, we can see that, among the three competitive products, product Z is a low-end but a strong player in the market. It possesses over half of the

market share. In contrast, the market share of the high-end product Y is about half of that of product Z. The middle-of-the line, product X, performs the worst in the market.

Next, we estimated the wholesale price of each existing competitive product using equations (6-8). On the basis of these estimated wholesale prices and the conjoint estimates, we estimated the marginal cost of production for each existing competitive product (based on equations 11-14). Our estimation results are shown in Table 6. In general, the retail margins obtained by the retailer are about 3 times of the wholesale margins charged by the manufacturers. This may be a reflection of the fact that the power balance in the distribution channel is in favor of the retailer.

<Insert Table 6 about here>

In order to assess the face validity of our model estimates, we acquired the retail margin and marginal cost estimates of these incumbent products from our industrial partner. These retail margin estimates are provided by the channel contacts of our industrial partner and by sources of competitive intelligence. Our estimates are reasonably close to the actual market margins[9]. Regarding the information about the marginal costs of production, the engineers at our industrial partner disassembled the incumbent products and estimated their variable unit costs by estimating the component, processing, and assembly requirements based on own cost structure. This is essentially the same idea as "reverse-engineering" discussed by Ulrich and Pearson (1998). Industrial experiences have shown that cost data estimates from this approach are normally very reliable (more discussion on this topic can be found at Ulrich and Pearson

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[9] An article in *Do It Yourself Retailing* (July 2004, p23) has a quote from a hardware store manager in Ohio that big box retailers in this industry normally charge between 15-20% as retail margin from the manufacturers. This also provides some external support for the face validity of our model estimates.

1998). We have found that these estimated variable unit costs are also within reasonable ranges from the estimates calculated from our model.

Next, we obtained information about the approximate market size in units of potential purchase from Power Tool Institute. In order to estimate the marginal shelf cost, we collected the category profit data in the year of 2003 through the market intelligence efforts of our industrial partner. We also calculated the category revenue during the same time period using the retail margin estimates and the market size data. The marginal shelf cost was then calculated as the difference between category revenue and category profit divided by the number of incumbent products. We assume constant marginal shelf cost here because there is no big difference in the size or weight of these products. The typical length of these products ranges from 10 to 12 inches. Typical weight of these products is between 3.5 to 4.5 pounds. Products beyond these ranges are normally classified as a different category since they have different usages and different feature sets. We recognize that, in reality, the marginal cost of retailing may not be a simple linear function of the number of units in the category. A more sophisticated model of marginal cost of retailing could be used here to enhance the predictability of channel acceptance. Finally, we calculated the retailer's category profit before new product entry using equation (9). All these estimates are shown in Table 6.

Overall, the demand, price, and cost estimates derived from our model are reasonably close to the market level data gathered through the market intelligence efforts of our industrial partner. This provides evidence of face validity. Our approach of modeling the market specifics before new product entry is appealing because it can be developed using just individual-level conjoint data and observable retail prices. Our

estimation after the entry of the new product is built upon the estimates presented above.

4.3 After New Product Entry

Given the selected product attributes and their levels of our conjoint experiment, the manufacturer of the new product has a total of 72 design alternatives (3 levels of amp rating, 3 levels of product life, 4 switch types, and 2 actuator types) they could potentially consider. Our estimates from the hierarchical Bayesian conjoint analysis indicated that about 80% of the respondents strongly prefer actuator A to actuator B, and the remaining 20% only slightly prefer actuator B to actuator A. Also, actuator B is more expensive to produce than actuator A. Therefore, the firm decided to choose actuator A in the design of the new product. Hence, the number of design alternatives considered by the firm was reduced to 36.

For each alternative, we calculated the Nash equilibrium wholesale and retail prices based on the iterative procedure described in the methodology section. When applying the gradient method to search for the profit-maximizing retail and wholesale prices, we evaluated the gradient vector after each iteration. If the sum of the absolute values of the four elements in the gradient vector is less than or equal to .01, we consider the iteration process to have converged. Adopting this convergence criterion led to essentially the same results as using tighter criteria, while greatly improving computational efficiency.

We calculated the retailer category profit for each design alternative at the estimated equilibrium prices. This category profit was compared to the category profit before the entry of the design alternative. If this profit is an increase over current profit, then the design alternative is retained. Otherwise, it is eliminated.

<Insert Table 7 about here>

Among the 36 design alternatives, 21 design alternatives do not increase the retailer's category profit and are removed from further consideration. Table 7 provides the approximate marginal cost of production, equilibrium retail and wholesale prices, and the status (retained or removed) for 5 selected design alternatives in our analysis. In this table, alternative number 3, number 7 and number 29 do not increase the category profit of the retailer at market equilibrium conditions. Therefore, they are eliminated from further consideration.

Our market scenario analysis for the introduction of the new product provides several insights. For all the 15 design alternatives that are predicted to increase the retailer's category profit, our market scenario analysis indicates that, at the market equilibrium conditions, the retailer's optimal behavior is to increase the retail prices charged for all existing products. Interestingly, this empirical finding is consistent with the prediction arising from Betancourt's (2004) analytical model that, if the products are gross substitutes, the retailer will charge higher retail prices for all existing items when a new item is added into the assortment. Intuitively, to be profitable for the retailer, these 15 design alternatives must either have a differentiated attribute space location, or be similar to the existing products but are offered at a lower price. From a social welfare perspective, the consumers must pay a price for such an improvement in the product assortment. Hence, the addition of such items provides the retailer an avenue to exploit additional profits; and one strategy for the retailer to maximize its category profit is to charge higher prices on existing products when broader assortment is offered. This effect is called "assortment effect" in Betancourt's (2004) model.

Another finding of our empirical analysis is that the profit maximizing behavior of the incumbent in response to new product entry is not always to lower its own wholesale price. In Table 7, entry of the new product results in lower equilibrium wholesale prices of all incumbent products only for alternative 16. For most of the cases, at the market equilibrium conditions, some incumbents choose to increase wholesale prices while the others choose to decrease wholesale prices (examples are alternative number 3, 7, 10, 29 in Table 7). This finding is consistent with Hauser and Shugan's (1983) analytical analysis of defensive marketing strategy. According to their analysis, a price increase may be optimal for the incumbents, depending on the distribution of the consumer tastes and the market segment that the new product is attacking.

Among the retained 15 design alternatives, alternative number 10 provides the highest profit for the manufacturer of the new product. The specification of alternative number 10 is: amp rating (6), life of product: 80 hours, top slider switch, actuator A, retail price at $81.65. When comparing this new product with the existing competitive products, this product seems to target at the low-end of the market and competes mostly with product Z. Considering that low-end product Z possesses the largest market share before new product entry, it is quite intuitive that one of the optimal strategies is to target the largest market segment at a favorable price. Also, the new product has a new type of switch (top slider switch), which is differentiated from all the switch types that are currently offered. This differentiation also helps to exploit some of the unmet consumer preferences.

With the introduction of this alternative, the market shares of product X, Y, Z will be 13.73%, 17.24%, and 33.12%, respectively. The market share of the new product will

be 16.15%. And the share of no purchase is predicted to be 19.76%. As we can see, the new product takes majority of the market share from product Z. Also, because the new product serves some of the unmet consumer demand before entry, the share of no purchase reduces from 24.9% (pre-entry) to 19.76% (post-entry).

According to our analysis, this design alternative will create $ 8.99 million in profit for the manufacturer of the new product. And the equilibrium category profit after the introduction of this new product for the retailer will be $71.22 million, which is an increase of $10.91 million in profit for the retailer as compared to current category profit.

The above analysis shows that the model we developed in this paper can be very useful for manufacturers of new products. Using only conjoint data and some general information about the competing manufacturers and the retailer, the managers of the new product development project can not only map out the optimal product positioning and pricing decisions, but also predict the market share and profit that will be brought by the new product. In particular, since we take the end users' needs, retailer's assortment, retailer's acceptance criteria, and competing manufacturers' potential reactions into consideration, the optimal new product derived from our model will have better chances of being accepted by the dominant retailers in the marketplace.

4.4 Comparison to a Naïve Model

In this section, we benchmark our proposed model with a naïve model. In this naïve model, the focal manufacturer selects the optimal new product without considering retailer acceptance. And the competing manufacturers and the retailer do not make any adjustments in prices in response to new product entry.

For all 36 design alternatives, the focal manufacturer charges a constant

wholesale margin of $6.68 (specified at market average level) and assumes a constant retail margin of $20.5 (specified at market average level) will be charged by the retailer. Next, the conjoint part-worths obtained from the hierarchical Bayesian estimation are used to estimate the market share of each new product alternative.

Among all the design alternatives, alternative number 17 provides the highest profit for the manufacturer of the new product. The specification of this design alternative is: amp rating (9), life of product: 150 hours, top slider switch, actuator A, retail price of $123.41. As we can see, in a comparison of our model and the naïve model, there are differences in the optimal designs. More importantly, under the naïve model, the chosen alternative will only provide $7.53 million in profit for the focal manufacturer and the retailer category profit after entry will only be $67.03 million dollars. In contrast, our model outputs an optimal design that can provide higher profits for both the focal manufacturer ($8.99 million) and the retailer ($71.22 million). Therefore, our model provides a win-win situation for both parties in the channel relationship as compared to this naïve model.

In the real marketplace, to the extent players in the market are strategic in their behavior, the market strategies undertaken by the retailer, the competing manufacturers, and the manufacturer of the new product are likely to be somewhere between our proposed model and this naïve model. These players in the distribution channel may learn over time and may adopt some sort of trial-and-error procedures to find the optimal market strategy. We believe that one of the contributions of our research is that we have provided a formal procedure to determine the optimal strategies not only for the manufacturers of the new product, but also for the retailers, because our model can also

educate the retailer how to charge optimal retail prices when faced with the introduction of a new product.

<center>5. Model Extensions</center>

In this section, we present several model extensions. In section 5.1, we consider the implication of our methodology in the scenario of a fixed category breadth. In section 5.2, we discuss a model extension in which the focal manufacturer introduces a new product to a category where it already has a product currently carried by the dominant retailer. In section 5.3, we illustrate a sensitivity analysis of our results to potential competitive reactions from the competing retailers.

5.1 Replacement of Competitive Products in the Channel

In this model extension, we consider the scenario in which the retailer considers replacing one existing product with the proposed new product. In this case, the retailer's optimal strategy will be to compare its equilibrium category profits before and after one existing product is replaced with the proposed new product.

Relating to our empirical application above, if the shelf space becomes extremely scarce, the dominant retailer may consider replacing one existing product with the proposed new product (alternative number 10 in our example) in a product line review. In order to account for such a scenario, we conduct analysis for three market scenarios. In each of the market scenario, one existing product (product X, product Y, or product Z) is replaced with alternative number 10. The equilibrium retail and wholesale prices arising from these three market scenario analyses are given in Table 8. As we can see from Table 8, since the retailer is not providing a broader assortment to the consumers in this scenario, the profit maximizing behavior for the retailer is not to increase the retail prices

of existing products anymore because the assortment effect disappears in such market scenarios.

<Insert Table 8 about here>

Among these three product assortments, the assortment {X, Y, New} provides the highest category profit at the market equilibrium conditions. At current level of marginal shelf cost, the category profit will be $51.97 million, which implies that replacing an existing product is not as profitable for the retailer as adding a new item in the category. However, if the marginal shelf cost increases significantly in the future, the optimal behavior for the retailer is to replace product Z with the new product. This model extension can also be very helpful for the manufacturer of the new product. When the dominant retailer calls for a product line review, the manufacturer of the new product will be able to use this model to identify the competitive product to bid against.

5.2 Product Line Extension of the Focal Manufacturer

In practice, manufacturers often have to face the problem of introducing new products into categories where they already have products. To account for this, we will need to revise the focal manufacturer's profit maximization function so that the manufacturer will choose a set of wholesale prices to maximize the profit it will obtain from the product line instead of a single product. For example, if already having an existing product carried by the dominant retailer, the focal manufacturer j would set two wholesale prices (w_{1j} for the existing product and w_{2j} for the new product) to maximize its profit, as described in equation (18):

$$\max_{\widetilde{w}_{1j}, \widetilde{w}_{2j}} \widetilde{\pi}_j^m = [(\widetilde{w}_{1j} - c_{1j}) * \widetilde{m}_{1j} + (\widetilde{w}_{2j} - c_{2j}) * \widetilde{m}_{2j}] * S - \widetilde{F}_j \qquad (18)$$

The first order conditions for the focal manufacturer would be:

$$\frac{\partial \tilde{\pi}_j^m}{\partial \tilde{w}_{1j}} = \tilde{m}_{1j} + (\tilde{w}_{1j} - c_{1j}) * \sum_{j'=1}^{J+1} \frac{\partial \tilde{m}_{1j}}{\partial \tilde{p}_{j'}} \frac{\partial \tilde{p}_{j'}}{\partial \tilde{w}_{1j}} + (\tilde{w}_{2j} - c_{2j}) * \sum_{j'=1}^{J+1} \frac{\partial \tilde{m}_{2j}}{\partial \tilde{p}_{j'}} \frac{\partial \tilde{p}_{j'}}{\partial \tilde{w}_{1j}} = 0 \quad (19a)$$

$$\frac{\partial \tilde{\pi}_j^m}{\partial \tilde{w}_{2j}} = (\tilde{w}_{1j} - c_{1j}) * \sum_{j'=1}^{J+1} \frac{\partial \tilde{m}_{1j}}{\partial \tilde{p}_{j'}} \frac{\partial \tilde{p}_{j'}}{\partial \tilde{w}_{2j}} + \tilde{m}_{2j} + (\tilde{w}_{2j} - c_{2j}) * \sum_{j'=1}^{J+1} \frac{\partial \tilde{m}_{2j}}{\partial \tilde{p}_{j'}} \frac{\partial \tilde{p}_{j'}}{\partial \tilde{w}_{2j}} = 0 \quad (19b)$$

Equations (19a) and (19b) could be combined with the competing manufacturers'
first order conditions to form a system of nonlinear equations with $J+1$ equations and $J+1$
unknown wholesale prices. The gradient method we described in the methodology
section could be used to solve for the profit-maximizing wholesale prices for all the
manufacturers. The retailer's profit-maximizing problem remains the same. Therefore,
our methodology could also be readily extended to study the optimal product line
positioning and pricing decisions of the manufacturers.

5.3 Sensitivity Analysis of Our Approach to Potential Reactions from Competing
Retailers

Given the focus of our application, we have explicitly modeled only one dominant
retailer in this study. Given the main goal of this research as predictive modeling and
scenario analysis, we now conduct some sensitivity analysis to test the robustness of our
approach to potential reactions from the competing retailers when the dominant retailer
adds a new product into its assortment.

Assuming that upon the addition of the optimal new product (alternative number
10) at the dominant retailer, the competing retailers decide to decrease the average retail
prices of their product offerings as a competitive move. In such a case, the attractiveness
of the outside goods increases. The market share of product j at the dominant retailer
becomes the expression in equation (20). We use "*" to represent the equilibrium prices

calculated from our model.

$$m_j = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(x_j^{'}\hat{\beta}_{ix} + p*_j\hat{\beta}_{ip})}{\sum_{j'=1}^{J+1}\left[\exp(x_{j'}^{'}\hat{\beta}_{ix} + p*_{j'}\hat{\beta}_{ip})\right] + \exp(\hat{a}_i + \hat{\beta}_{ip}\Delta p)} \quad j=1,...,J+1 \quad (20)$$

Where Δp = the average decrease in retail prices of the competing retailers' offerings.

As we can see from equation (20), if Δp is large, the dominant retailer will lose a big portion of its market to the competing retailers and adding alternative number 10 may make the retailer worse-off. This only happens when the competing retailers respond fiercely to the category expansion of the dominant retailer. In contrast, if Δp is small enough, the dominant retailer will obtain a higher category profit by expanding its assortment, even if the competing retailers respond by price adjustments. By observing equation (20), we know that there is a value of Δp making the dominant retailer indifferent between adding this new product and not adding it. Now we describe how to calculate this value of Δp.

We first substitute the expression of m_j in equation (20) into the dominant retailer's category profit function. Next, we solve for a value of Δp to satisfy the equality in equation (21), with π^{r*} representing the dominant retailer's category profit before new product entry. Given the fact that the sign of $\hat{\beta}_{ip}$ is negative across respondents, the left hand side of this equality is a strict decreasing function of the absolute value of Δp. Therefore, the numerical solution to equation (21) can be easily found.

$$\sum_{j=1}^{J+1}\left[\left(\frac{1}{N}\sum_{i=1}^{N}\frac{\exp(x_j^{'}\hat{\beta}_{ix} + p*_j\hat{\beta}_{ip})}{\sum_{j'=1}^{J+1}\left[\exp(x_{j'}^{'}\hat{\beta}_{ix} + p*_{j'}\hat{\beta}_{ip})\right] + \exp(\hat{a}_i + \hat{\beta}_{ip}\Delta p)}\right)*(p*_j - w*_j)\right]*S - sc*(J+1) = \pi^{r*}$$

$$(21)$$

For our application, this breakeven value of Δp is -$5.4. Namely, the optimal product selected by our methodology and the equilibrium retail prices calculated by our model will still bring additional profit for the retailer, even if the competing retailers decide to respond by a price cut, as long as the average price cut is less than $5.4.

This robustness measure of our approach is also conservative because, in reality, it is not likely that all consumers will have full price information of all the product offerings on the market (Simester 1995). As a result, being the first place most consumers shop gives the dominant retailer a natural advantage even in the face of price decrease from the competing retailers (Wernerfelt 1991).

6. Conclusions and Future Research

Our research has developed a methodology that will help manufacturers to directly account for the acceptance criteria of dominant retailers in selecting optimal new products. The methodology also accounts for individual-level consumer preferences, the retailer's existing product assortment, and the retailer's and the competing manufacturers' potential price reactions in response to the entry of the new product. Therefore, our proposed model has the ability to forecast different market scenarios and predict the market shares and profits associated with different design alternatives with the likely retailer and competitive reactions already factored into the scenarios. To our knowledge, there is currently no formal procedure in the marketing literature like the one proposed in this paper.

Our methodology can lead to the development of a rigorous theoretically-grounded decision support system (DSS) to aid managers in selecting new product designs. The market scenarios can also be very helpful in targeting a specific competitor

product for replacement in the retailer's assortment when retailers call for a product line review (which powerful retailers are increasingly resorting to). In addition, the DSS can help manufacturers of the new products in supporting their negotiations for market entry with the dominant retailers. Furthermore, we believe that our methodology can be used as a category management tool to educate the retailers as to how to make adjustments in the retail prices of existing products and how to charge an optimal retail price in response to the introduction of a new product. As a result, the manufacturers adopting this methodology can use it as a tool to convince the big-box retailers to involve them in the retailer's category management, which will have valuable long-term impact on the profitability of the manufacturers.

Regarding the applications of our methodology, it might be useful to include store brands into our framework, given the increasing number of store brands in the marketplace (the retailer in our focal application does not sell store brands in the category studied). Our model can be easily extended to account for store brands by revising the retailer's profit function to include the profit it will obtain from the store brand. For the store brand, the retailer's decision is to select the optimal retail price given the marginal cost of the product. And the decision rules for the other products remain the same.

We believe that the methodology introduced in this paper provides a starting point for marketing academia and practitioners to study the topic of new product development under channel acceptance. Given the vast consolidation of retailers and fast proliferation of new products in the market place, it is time for manufacturers to seriously consider the issue of channel acceptance before new product introductions.

Future research can extend our approach to analyze a variety of other settings of

interest. For example, an extension of our model could be developed to examine the optimal product positioning and pricing strategy in channels with two-part pricing, quantity discounts, or slotting allowances as common practice. Under such institutional settings, a combination of category management and channel coordination should be incorporated as the retailer and the manufacturers' objective functions. In addition, for markets where a few big-box retailers each possess a similar share of the distribution, an extension of our framework that derives the optimal new product positioning and pricing strategy under retail equilibrium as well as manufacturer equilibrium would be valuable. Finally, there is a need for a model with a long-term pure strategy equilibrium of both product positioning and pricing. Even though a pure strategy equilibrium does not generically exist for the case of uniform pricing strategy (Anderson, de Palma, and Thisse 1992), alternative pricing structures and functional forms of consumer demand may be used to derive a desirable location equilibrium in pure strategies.

ESSAY 2: CONSUMER INFERENCES IN PRODUCT DESIGN AND EVALUATIONS

ABSTRACT

In a retail store environment, consumers often evaluate a product based on its overall attractiveness. For example, the users of power tools may evaluate a power tool based on not only its objective product attributes such as brand, price, or switch type but also its subjective characteristics such as whether the tool feels sturdy and easy to use. However, existing studies of consumer preferences such as conjoint models are limited in incorporating the influence of these subjective characteristics into product design and evaluations (Srinivasan, Lovejoy, and Beach 1997).

In this study, we use customer-ready prototypes to examine whether the consumers use the objective product attributes (such as shape and switch type) as cues to make inferences about the subjective characteristics (such as comfort) of the product, and whether both the objective product attributes and the subjective characteristics jointly affect consumer's evaluations towards products. The proposed model has the form of a Hierarchical Bayesian path analysis model that incorporates the impact of both the objective product attributes and the subjective characteristics on the estimation of individual-level consumer preferences. By incorporating additional information about consumers' ratings for the subjective product characteristics into the estimation procedure, our model is able to provide the designer with better understanding and prediction of consumers' evaluations towards different product design candidates, as compared to a traditional conjoint model.

We illustrate our approach in two studies. The first study was conducted in the context of a new power tool development project undertaken by a US manufacturer. The

second study was conducted on toothbrush category to further support the validity and

generality of our model.

1. Introduction

Understanding how consumers evaluate a product is an important issue in any market-driven product design process. In a retail store environment, consumers often evaluate a product based on its overall attractiveness. For example, the users of a drill may evaluate it based on not only its objective product attributes such as brand, price, or switch type but also its subjective characteristics such as whether the tool feels sturdy and easy to use. Similarly, the determinant factors of an automobile purchase may be both its subjective characteristics such as emotional appeal and its objective attributes such as gas mileage.

However, most existing studies of product design assume that the consumer evaluates a product only in terms of its objective product attributes. In a typical conjoint-based product design procedure, consumers' preferences are estimated through their overall evaluations of a set of hypothetical product concepts that are defined in terms of different levels of different attributes. Estimated individual or aggregate level part-worth utilities are then used to estimate consumers' preferences towards different product design candidates. As pointed out by Srinivasan, Lovejoy, and Beach (1997), even though some subjective characteristics of the product such as ergonomics and integrity exert important influence on consumer's evaluation towards the products, traditional attribute-based conjoint methods are very limited in capturing such impact.

Although, in theory, we can include some objective product characteristics (such as defining three levels of "perceived comfort" as: "more comfortable than average", "average comfort level", and "below average in terms of comfort") in a conjoint experiment, it is difficult for the product designer to make any use of such conjoint

estimates. First, the notion of an average may be different for different customers. Second, such a product characteristic cannot be made directly "actionable" from the designer's viewpoint.   Specifically, from the designer's perspective, the perceived comfort of a product may be jointly determined by its shape, weight, and some other features of the product. Thus, in order to manipulate the levels of such an attribute in a design, the designer needs to identify the impact of various product attributes on consumers' perceptions towards the perceived comfort level of the product. Unfortunately, existing conjoint methods do not offer such information. Several previous studies (such as Griffin and Hauser 1993; Gupta and Lord 1995; Hauser and Clausing 1988; Narasimhan and Sen 1989; Neslin 1989) have attempted to establish the link between the concrete, quantifiable product attributes to consumers' perceptions of the abstract, qualitative aspects of the product. However, none of these studies investigate how to incorporate the impact of these subjective product characteristics into the selection of optimal product design.

Surprisingly, there is currently no formal procedure readily available to help product designers to incorporate the joint impact of objective product attributes and subjective product characteristics into optimal product design and evaluation. To the best of our knowledge, the paper by Tybout and Hauser (1981) is the only study that has attempted to consider consumer choice as a function of a combination of physical attributes and consumer perceptions. In this study, however, the link between the physical attributes and consumer perceptions was not addressed.

The main goal of our research is to propose a methodology to connect the objective product attributes to the subjective product characteristics, and furthermore, to

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incorporate consumer's perceptions about the subjective characteristics into the process of product design and evaluation. We examine whether the consumers use the objective product attributes (such as shape and switch type) as cues to make inferences about the subjective characteristics (such as comfort) of the product, and whether both the objective product attributes and the subjective characteristics jointly affect consumer's evaluations towards products.

Unlike traditional methods in product design, we use customer-ready prototypes rather than hypothetical product concepts in our experiments. In such a setting, our subjects are able to touch and feel the products (similar to the scenario in a retail store environment) and evaluate their overall attractiveness based on not only the objective attributes such as price, shape, weight as well as the subjective characteristics such perceived comfort and perceived power. The subjects were first asked to indicate their likelihood of purchasing each prototype. Following this, the subjects were asked to provide ratings for some of the subjective characteristics of these prototypes

A Hierarchical Bayesian path analysis model is used to decompose the joint impact of the objective product attributes and subjective product characteristics on consumer's preference for the prototypes. There are several important advantages of using such a model for our research. First, the method of path analysis allows us to simultaneously examine the causal effects in a system of equations. As pointed out by Tybout and Hauser (1981), consumer perceptions of the subjective product characteristics are often abstractions of the objective product attributes. A simple model of consumer preference with both objective attributes and subjective characteristics as predictors of choice is subject to the problem of multi-collinearity. To address this issue,

we adopt a system of equations in which the objective product attributes are predictors of the subjective product characteristics, and a combination of these attributes and characteristics jointly affects consumer's evaluations of a prototype.

Second, we use Bayesian methods to estimate consumer heterogeneity. Using power tools as an example, different consumers may prefer different shapes or different switch types. And the impact of different shapes and switch types on perceived comfort of the product may be different across different consumers. As a result, it is important to use Bayesian estimation to obtain individual-level consumer estimates in our path analysis model.

Finally, an important managerial implication of our model is that we can use our individual level model estimates to predict consumer perception for products that are currently in conceptual form. By including the predicted consumer perception on the subjective characteristics as well as the objective product attributes, we can help the managers to make a more accurate forecast of consumer's purchase likelihood for not only existing prototypes but also products that exist in conceptual form. One major concern of using prototypes at the early stage of new product development is the cost of carrying multiple product concepts forward into customer-ready status. Our approach provides a very practical solution to this problem. Product designers could gather a handful of existing products available on the market or produce several prototypes in the lab and use our method to enhance their selection of optimal product design.

We have also benchmarked our method against traditional Hierarchical Bayesian Rating-Based Conjoint models. We have found that our model outperforms the conjoint model in providing the designer with better understanding and prediction of consumers'

evaluations towards different product design candidates.

The rest of this paper is organized as follows. In the next section we provide a discussion of relevant previous research. In Section 3, we present the details of our model. Section 4 illustrates two empirical applications of this approach. This paper concludes with conclusions and discussions.

<div align="center">2. Relevant Previous Research</div>

2.1 Decompositional Preference Measurement

In the marketing literature, there have been three main approaches to measure consumer preference: (1) compositional approach; (2) decompositional approach; and (3) a hybrid of compositional and decompositional approach (Green and Srinivasan 1990). The method we present in this study belongs to the branch of decompositional approach. In this stream of research, conjoint methods have been widely used in the field of new product development.

Traditional conjoint methods comprise the following steps: (1) specify product attributes and levels associated with each attribute; (2) build many product profiles based upon the specified product attributes and levels; (3) ask respondents to rate/rank each product profile; and (4) calculate the utility value associated with each attribute level based on the respondents' evaluations of the product profiles.

The strengths of the conjoint methods include their systematic and self-consistent nature, which is enforced by their mathematical representation. However, the critical assumptions underlying these methods are: (1) consumer preference is solely a function of quantifiable product attributes and (2) these attributes can be represented in the form of hypothetical product concepts. Several researchers have questioned these two

assumptions. For example, Srinivasan, Lovejoy, and Beach's (1997) work suggests that, even though typically not included in conjoint experiment, several important qualitative aspects of the product (such as aesthetics and emotional appeal; ergonomics and usability) have significant impact on consumer preferences. Dr. Gerald M. Mulenburg, Chief of Aeronautics and Spaceflight Hardware Development Division at NASA, has also pointed out that "it is far easier for clients to articulate what they want by playing with prototypes than by enumerating requirements". According to him, NASA has continued to use prototypes in developing new products with great success (*Vision*, cover story, October 2004).

To address their critique on traditional conjoint methods, Srinivasan et al. (1997) suggest a road map for integrated product development that leverages the attribute-based customer preference and the non attribute-based customer preference. Their proposed process, however, does not address the link between consumer perceptions on the subjective characteristics of the product and the objective product attributes. From the product designer's point of view, it is important to understand how different combinations of objective product attributes (such as price levels, shapes, and weight levels) contribute to consumer's perception of the subjective characteristics of the product (such as whether or not the product is powerful). However, existing decompositional preference measurement approaches such as conjoint methods cannot provide such information.

To address this problem, we use a hierarchical Bayesian path analysis model to decompose the joint impact of the objective product attributes and the subjective product characteristics in the following way. First, we hypothesize that the consumer uses the

objective product attributes (such as shape and switch type) as cues to make inferences about the subjective characteristics of the product (such as perceived comfort). Second, we examine how these subjective product characteristics are combined with the objective product attributes in determining the consumer preference. Finally, we estimate these relationships simultaneously in a system of equations with individual-level estimates to address consumer heterogeneity.

2.2 The Link from Objective Product Attributes to Subjective Product Characteristics

Marketing researchers have long recognized the importance of understanding the linkage between the objective product attributes and consumer's perceptions on the subjective characteristics of the product. For example, Neslin (1981) attempted to link product features to perceptions to gain an ability to predict how perceptions change as feature combinations are altered. He has found that a regression model with perception as dependent variable and product features as predictors outperforms the self-stated (compositional) model. Neslin (1981) also reported that adding interaction effects does little to improve the predictive ability of the model. Similarly, Gupta and Lord (1995) have run regressions on data collected from an automobile survey with objective product attributes (such as rear leg room and acceleration) as independent variables and consumer perceptions on the subjective characteristics of the car (such as luxury and comfort) as dependent variables. They have found that consumer perceptions on the subjective product characteristics are well represented by the objective product attributes.

Another related stream of research in this area is the "house of quality" model proposed by Hauser and Clausing (1988) and Griffin and Hauser (1993). Both our model and the "house of quality" model investigate the relationships between design attributes

and the qualitative aspects of the product. However, the two models have different

focuses. The "house of quality" model focuses on understanding the interrelationship

between engineering attributes and consumer perceptions. In contrast, our model focuses

on incorporating the relationship between objective attributes and subjective

characteristics into consumer's product evaluation process and helping product designers

to select optimal product designs.

In the consumer research literature, researchers have found that consumers make

inferences about the unobservable product attributes or characteristics during the

evaluation process (Huber and McCann, 1982; Johnson and Levin, 1985; and Ross and

Creyer, 1992). The findings of Huber and McCann (1982) are of particular relevance to

our study. Their research indicates that the decision makers infer values of the

unobservable product characteristics whereby the visible attributes serve as cues that the

consumers use to make inference. And these inferred characteristics are combined with

the observable attributes to form consumer preferences or choice. In Huber and

McCann's (1982) experiment, subjects are asked to evaluate their purchase likelihood of

a number of profiles describing different beers. Each beer is described either by two

attributes (price and quality) or one attribute (either price or quality). Half of the subjects

are asked to make inferences about the value of the missing attribute, and half are not.

Huber and McCann (1982) have found that, even without prompting, consumers

spontaneously make inferences about the value of the missing attribute and the imputed

value is integrated with the available attribute information into the product evaluation.

Building upon existing research in this area, we hypothesize that consumers make

inferences about the underlying subjective characteristics of the product (such as perceive

power) based on the objective product attributes (such as shape and price). We posit that, when evaluating a product, consumers may use the objective product attributes as cues to infer the subjective characteristics of the product. Therefore, consumer perceptions on the subjective characteristics are combined with the objective product attributes to form the basis for product evaluation.

In the next section, we provide a detailed description of our methodology.

3. Model Development

We employ a Hierarchical Bayesian Path Analysis model in this paper. An outline of our model is schematically shown in Figure 4, using the product design and evaluation of a power tool as an example (study one in our empirical application).

<Insert Figure 4 about here>

In Figure 4, we use boxes to represent independent variables and ovals to represent dependent variables. The boxes in the left column of Figure 4 represent a set of objective product attributes (namely. price, weight, shape types, and switch types). The ovals in the middle column of Figure 4 represent consumer perceptions on subjective characteristics of the product (i.e. perceived power and perceived comfort). The oval in the right column of Figure 4 represents the purchase likelihood of the consumer.

As we can see, in Figure 4, the objective product attributes are defined at different levels. Three price levels are considered (p_1, p_2, p_3), along with two levels of product weight (w_1, w_2), three types of product shapes (sh_1, sh_2, sh_3) and four switch types (sw_1, sw_2, sw_3, sw_4). This is similar to the common setting in conjoint experiments. All these attributes are coded as effect-type dummy variables with ones representing the corresponding product attribute level of each prototype. In order for the model to be

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identified, we omit the first level of each attribute in the estimation and the path coefficient associated with this attribute level is treated as zero.

In Figure 4, perceived power is defined as function of price, weight, and shape of the product. And perceived comfort is a function of weight, shape, and switch type of the product. Following previous research (Gupta and Lord 1995; Neslin 1981), the relationships between the objective product attributes and consumer's perception on the subjective product characteristics are established by two separate stepwise regressions. In each regression, consumer's perception (e.g. perceived power) is defined as the dependent variable and all the objective product attributes (i.e. price, weight, shape, and switch type) are initially included as predictors. Using stepwise estimation, some predictors are dropped out if their additional explanatory power is not significant. In this example, we have found that switch type does not have significant impact on perceived power and price does not have significant impact on perceived comfort. Hence, we have the model outlined in Figure 4. Another avenue to establish the relationship between the objective product attributes and the subjective characteristics is through exploratory research such as focus group studies.

Once the relationship between the objective attributes and subjective characteristics is defined, we use a Hierarchical Bayesian Path Analysis model to estimate the model presented in Figure 4. We begin by presenting the individual-level model specifications. Let us denote that, for individual i, the perceived power towards prototype s is represented as pwr_{is}, perceived comfort for this prototype is cft_{is}, and purchase likelihood for prototype s is specified as pll_{is}. We assume that these variables are normally distributed as follows:

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$$pwr_{is} \sim N(\mu_{\alpha is}, \sigma_\alpha^2) \quad i=1,\ldots,I; \; s=1,\ldots,S \qquad (1a)$$

$$cft_{is} \sim N(\mu_{\beta is}, \sigma_\beta^2) \qquad i=1,\ldots,I; \; s=1,\ldots,S \qquad (1b)$$

$$ppl_{is} \sim N(\mu_{\gamma is}, \sigma_\gamma^2) \qquad i=1,\ldots,I; \; s=1,\ldots,S \qquad (1c)$$

The mean parameters $\mu_{\alpha is}$, $\mu_{\beta is}$, and $\mu_{\gamma is}$ in equations (1a-1c) have the following specifications:

$$\mu_{\alpha is} = \alpha_{oi} + \alpha_{1i} p_{2is} + \alpha_{2i} p_{3is} + \alpha_{3i} w_{2is} + \alpha_{4i} sh_{2is} + \alpha_{5i} sh_{3is} \qquad (2a)$$

$$\mu_{\beta is} = \beta_{oi} + \beta_{1i} w_{2is} + \beta_{2i} sh_{2is} + \beta_{3i} sh_{3is} + \beta_{4i} sw_{2is} + \beta_{5i} sw_{3is} + \beta_{6i} sw_{4is} \qquad (2b)$$

$$\mu_{\gamma is} = \gamma_{oi} + \gamma_{1i} p_{2is} + \gamma_{2i} p_{3is} + \gamma_{3i} w_{2is} + \gamma_{4i} sh_{2is} + \gamma_{5i} sh_{3is} + \gamma_{6i} sw_{2is} + \gamma_{7i} sw_{3is} + \gamma_{8i} sw_{4is}$$
$$+ \gamma_{9i} pwr_{is} + \gamma_{10i} cft_{is}$$

(2c)

At the population level, we assume the following multivariate normal distributions for the following parameters:

$$(\alpha_{i0}, \alpha_{i1}, \ldots, \alpha_{i5}) \sim MNorm(\Theta_\alpha, \Omega_\alpha) \qquad i=1,\ldots,I \quad (3a)$$

$$(\beta_{i0}, \beta_{i1}, \ldots, \beta_{i6}) \sim MNorm(\Theta_\beta, \Omega_\beta) \qquad i=1,\ldots,I \quad (3b)$$

$$(\gamma_{i0}, \gamma_{i1}, \ldots, \gamma_{i10}) \sim MNorm(\Theta_\gamma, \Omega_\gamma) \qquad i=1,\ldots,I \quad (3c)$$

Next, we specify some diffuse but proper distributions for the set of hyper-priors. Three conjugate gamma distributions are specified for $\sigma_\alpha^2, \sigma_\beta^2, \sigma_\gamma^2$. Three multivariate normal distributions are assumed for $\Theta_\alpha, \Theta_\beta, \Theta_\gamma$. And three inverse Wishart distributions are specified for $\Omega_\alpha, \Omega_\beta, \Omega_\gamma$. The selected distributions for hyper-priors have shown to be very flexible and reasonable in the Bayesian literature (e.g. Arora, Allenby, and Ginter 1998; Neelamegham and Chintagunta 1999).

We implement this model in Winbugs 1.4.1. The model is estimated by the Gibbs Sampler using the Metropolis-Hastings algorithm to simulate draws from the full conditional distribution of the model parameters. As compared to traditional conjoint methods, our model has several important advantages.

First, our model estimates $\alpha_{0i}, \alpha_{1i}, ..., \alpha_{5i}$ and $\beta_{0i}, \beta_{1i}, ..., \beta_{6i}$ (for $i = 1, ..., I$) will help us to predict how consumer perceptions on the subjective characteristics of the products change as the objective product attribute combinations are changed. As a result, we gain ability to discover how implementing one level of product attribute rather than another will affect consumer perceptions. This estimation also takes individual heterogeneity into account. Therefore, our model can provide the product designer more diagnostic information hence enhance his/her managerial decision.

Second, more importantly, we can incorporate the information of the predicted consumer perceptions into the forecast of purchase likelihood for different combinations of objective product attributes, including products that are currently in conceptual form. The prediction can be done as follows. We first construct a set of design alternatives by enumerating all the possible combinations of objective product attribute levels. Next, we use equations (2a) and (2b) to estimate each individual's perceptions on the perceived power and perceived comfort of each design candidate. Third, the estimated consumer perceptions are employed into equation (2c), along with our model estimates $\gamma_{0i}, \gamma_{1i}, ..., \gamma_{10i}$ (for $i = 1, ..., I$), to make forecast on each individual's purchase likelihood for each design candidate. Finally, we take the average of the individual-level estimates on purchase likelihood for each design candidate. The optimal product design is selected

as the one having the highest overall purchase likelihood[10].

We also benchmark our proposed model against a traditional Hierarchical Bayesian Rating-Based Conjoint model. If we eliminate the subjective product characteristics ("perceived power" and "perceived comfort") as predictors of purchase likelihood and remove all the dotted arrows from Figure 4, the reduced model becomes identical to a traditional conjoint model that uses prototypes for stimulus presentation. Mathematically, this model can be expressed as follows, with all distribution assumptions on the priors and hyper-priors remaining the same as described above.

$$\mu_{\gamma is} = \gamma_{oi} + \gamma_{1i} p_{2is} + \gamma_{2i} p_{3is} + \gamma_{3i} w_{2is} + \gamma_{4i} sh_{2is} + \gamma_{5i} sh_{3is} + \gamma_{6i} sw_{2is} + \gamma_{7i} sw_{3is} + \gamma_{8i} sw_{4is} \quad (4)$$

Several comparisons can be conducted between our proposed model and the traditional conjoint model. First, we can use a Bayesian measure of model fit called as Deviance Information Criterion (DIC) to compare the short-term predictive ability of the two models on consumer's purchase likelihood (Spiegelhalter, Best, Carlin, and Linde 2002). The model with the smaller DIC is considered to be the one that would make better predictions on a replicate dataset. The DIC measure is defined as follows:

$$DIC = \hat{D} + 2 * P_D \quad (5)$$

In equation (5), $\hat{D} = -2 * \log(\dfrac{\Pr(\hat{\theta}|y)}{\Pr(\hat{\theta})})$ is the deviance of the posterior means in which y represents all the stochastic variables (i.e. the dependent variables in our model) and $\hat{\theta}$ represents the posterior parameters upon which the distribution of y depends. And

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[10] Previous research by Jamieson and Bass (1989) has indicated difference between stated intention and actual behavior of the consumers. We recognize that our forecast of purchase likelihood is subject to such bias. Stated intentions could be adjusted to improve predictive accuracy by incorporating exogenous measures such as liking, affordability, availability etc. Due to the lack of required data, we did not pursue this refinement.

P_D stands for the effective number of parameters with the expression

$$P_D = E_{\theta|y}[(-2) * \log\left\{\frac{\Pr(\theta|y)}{\Pr(\theta)}\right\}] + 2 * \log\left\{\frac{\Pr(\hat{\theta}|y)}{\Pr(\hat{\theta})}\right\}$$ where the first component of the

equation represents the posterior mean of the deviance and the second component

represents the deviance of the posterior mean.

If consumer's perceptions on the subjective product characteristics and the

objective product attributes have a joint impact on consumer's preference towards the

product, our proposed model should have a smaller DIC value on consumer's purchase

likelihood estimation, as compared to a traditional conjoint model.

Second, in addition to assessing the in-sample model fit, we could compare the

mean absolute error (MAE) between the actual individual-level purchase likelihood and

the predicted individual-level purchase likelihood on holdout samples. We hypothesize

that the estimates from our proposed model will have smaller MAE on holdout samples

as compared to the traditional model.

Finally, without considering the unobserved mediating effect of the subjective

product characteristics, the traditional conjoint model may misidentify the optimal

product design for a given sample of consumers. For example, if we define consumer's

purchase likelihood as a function of only the objective product attributes, the traditional

conjoint method may indicate that the optimal product design should adopt shape B,

because the estimated direct impact of shape B on purchase likelihood is superior to

shape A and shape C. However, because product shape also affects consumer's

perceptions on perceived power and perceived comfort, which in turn influence purchase

likelihood, the true impact of different shapes on purchase likelihood may be either

underestimated or overestimated in a traditional conjoint model. As a result, the shape of the product identified as "most preferred" by the conjoint model may not necessarily be the shape in the product actually preferred most by the end users. In contrast, our proposed model will help to eliminate such misidentification in the design of the new product.

4. Empirical Applications

In this section, we illustrate our approach using two studies. The first study was conducted in the context of a new power tool development project undertaken by a US manufacturer. The second study was conducted using the toothbrush category to further support the validity and generality of our model. In section 4.1, we describe the empirical results obtained from study one. In section 4.2, the estimation results from study two are presented.

4.1 Study One: Design of a Handheld Power Tool

The data for this study were collected from construction workers and metal workers recruited from various job and construction sites in a large metropolitan area. Our data set consists of 510 observations across 51 participants. The experiments were conducted in the field and each experiment session lasted approximately 45 minutes. Each participant was asked to evaluate 10 customer-ready prototypes. Among them, the data obtained from 9 prototypes were used for calibration and the evaluation on the last prototype was used for holdout validation. Our experiment consists of two stages as follows:

4.1.1. Stage One: Inference Unprompted

Stage one of the experiment is identical to a traditional conjoint experiment with

prototypes as stimulus presentation. We employ this experimental setting for two reasons. First, this setup is very similar to the situation of consumers inspecting different products in a retail store environment. The participants were presented with 10 prototypes with a price tag attached to each product. They were asked to imagine that they were shopping for this type of power tool in a retail store. The respondents had an opportunity to touch and feel each prototype before they provided their likelihood of purchase for each prototype based on its overall appeal. According to previous research (Huber and McCann 1982), the prompting of inferences can significantly alter consumers' preferences. In our study, we are interested in whether consumers make spontaneous inferences on the subjective product characteristics without any prompting. Therefore, we purposely did not ask subjects about their opinions about any of the subjective characteristics of the prototypes at this stage. The second reason for using this experimental setup is that it helps us to make valid comparisons between the traditional conjoint model and the proposed model in terms of model fit and predictive ability.

Table 10 provides a complete list of objective product attributes and the corresponding attribute levels for this power tool design study. Based on exploratory research and field experiences, we selected this specific set of objective product attributes as they were considered most salient when end users evaluated the product on multiple dimensions. Brand was not included as one attribute because our main interest is to select the most preferred product design among a set of design candidates with the same brand name. Even though brand name may have some impact on consumer's perceptions on the product, such impact is identical across all design candidates. Given these attribute levels, we use orthogonal design criterion to construct 9 product profiles. We also

calculated the D-efficiency for our experimental design (Kuhfeld, Tobias, and Garratt 1994). As a measurement for orthogonal and balanced experimental design, D-efficiency is defined as follows:

$$D - efficiency = \frac{100}{N * \left| (X'X)^{-1} \right|^{1/k}} \qquad (6)$$

Where N represents number of tasks, k stands for number of attributes and X is the design matrix using effects-type dummy variable coding. Even though a perfect experimental design will have an efficiency of 100, it is not always possible given the number of attribute levels and the numbers of tasks we could provide to the respondents. Our experimental design provides a D-efficiency of 73.89, which is acceptable in most empirical studies.

<Insert Table 10 about here>

Next, we took these product profiles along with one additional profile for holdout validation to the industrial design lab of our industrial partner. With the help of the mechanical engineers in the lab, ten customer-ready prototypes were produced for this study. All these prototypes are painted grey. A single-concept conjoint experiment was used for this study. For each of the ten prototypes, the subjects were asked to indicate their likelihood of purchasing the prototype on a 11-point scale anchored at "extremely unlikely" and "extremely likely".

4.1.2 Stage Two: Inference Prompted

In stage two, the respondents were asked to rate each of the ten prototypes on the measures of perceived power and perceived comfort in use. We used a 3-item measurement on a 7-point scale ranging from "strongly disagree" to "strongly agree" to

measure perceived power (i.e. "I expect this grinder to be powerful"; "This grinder feels weak" (reverse coding); "This grinder may not be powerful enough to do my job" (reverse coding)). A 4-item measurement scale was used to measure perceived comfort (i.e. "The grip of this grinder feels comfortable"; "This grinder feels balanced"; "This grinder is difficult to use" (reverse coding); and "The configuration of this grinder will allow me to do my job without any kind of obstruction"). A pilot study with 80 observations across 8 respondents was conducted to assess the validity and reliability of the measurement scales. The discriminant validity of these scales was testified through confirmatory factor analysis. The Cronbach's alpha for perceived power is .778 and perceived comfort is .747.

4.1.3 Model Estimation Results

We first conducted Bayesian estimation on the model specified in equations (1-3). Following the convention in Rating-Based conjoint model, we adopted logit recoding on the purchase likelihood data to facilitate meaningful interpretation on the estimation results (see *Sawtooth CVA User's Manual*). We first divide the numerical purchase likelihood responses by 12 so that the raw purchase likelihood data are mapped to probabilities. Then, we perform logit transformation on the calculated probabilities (i.e. $pll = \ln[pr/(1-pr)]$, with pr representing probabilities). One advantage of such transformation is that, when we perform market forecasts, the antilog of the estimated utility sum is equal to expected likelihoods of purchase (i.e. $pr = \exp(u)/(1+\exp(u))$, with u representing the calculated utility sum for each design alternative).

We ran two parallel Monte Carlo Markov Chains with random selected initials to assess the convergence of the Gibbs sampler. We monitored the on-screen display of the

traces from each chain for each parameter. 6,000 iterations from each chain were used as burn-in. The next 10,000 iterations from each chain were used to obtain the posterior means and standard deviations of the parameter estimates. A skip factor of 10 was chosen to compensate for the fact that successive draws of the posterior estimates may not be independent. Therefore, 2,000 draws were used to construct the posterior parameter estimates.

In Table 11, we provide the parameter estimates of perceived power (equation 2a) for 5 randomly selected respondents in our sample. Our stepwise regression has identified that perceive power is a function of product shape, weight, and price of the product. As we can see, there is a considerable amount of heterogeneity across the respondents in their perceptions on which type of product shape is powerful. With regard to product weight and price, in general, heavy weight and higher price contribute to a positive perception on the perceive power of the product. However, the magnitude of such impact is stronger for some respondents while weaker for others.

<Insert Table 11 about here>

In Table 12, the parameter estimates of perceived comfort (equation 2b) for the same 5 randomly selected respondents are provided. Our stepwise regression has indicated that perceive comfort is a function of product shape, switch type, and weight of the product. Similarly, we observe a large amount of heterogeneity across the respondents in their perceptions on which type of product shape and which switch type is comfortable to use. If we compare the parameter estimates for different shapes in Table 11 and Table 12, one interesting fact is that, for the same respondent, one shape type may be considered as the worst on one dimension of consumer perception while the best on

other dimension. For example, for respondent #18, shape 3 is considered to be worse than shape 1 and shape 2 in perceived comfort. Meanwhile, this shape is also perceived to be more powerful than the other two shapes. In this case, the overall preferences of respondent #18 for these three different product shapes are determined not only by their direct influences on purchase likelihood but also by their indirect impact through perceive power and perceived comfort and how much this respondent values these two perceptions. In contrast, traditional conjoint model only models the direct impact of shape on purchase likelihood, which may lead to either overestimation or underestimation of the true effect. With regard to product weight, heavy weight has a negative impact on perceive comfort in general. And the magnitude of this negative association is stronger for some respondents while weaker for others. In a comparison between Table 11 and Table 12, we can see that most respondents perceive a heavy weight product to be powerful but not very comfortable to use. Therefore, the optimal product for a consumer may be either heavy or light, depending on how much he/she values between power and comfort.

<Insert Table 12 about here>

In Table 13, we present the parameter estimates of purchase likelihood (equation 2c) for the 5 randomly selected respondents. In our model, purchase likelihood is defined as a function of all the objective product attributes, perceived power, and perceived comfort. Table 13 shows that the subjective product characteristics do not completely mediate the impact of objective product attributes on purchase likelihood. As we predicted, the subjective characteristics are combined with the objective product attributes to influence consumer's evaluation towards the product. In addition, the overall

pattern indicates that most power tool users emphasize more on perceived comfort than perceived power when it comes to purchase decisions. Such diagnostic information is very useful for product designers in making managerial decisions.

<Insert Table 13 about here>

In Table 14, we provide parameter estimates obtained from traditional Hierarchical Bayesian Rating-Based conjoint model (equation 4) for the 5 randomly selected respondents. We cannot directly compare the parameter estimates between Table 13 and Table 14 because of the mediating impact of perceived power and perceived comfort. However, we can compare the DIC (Deviance Information Criterion) value calculated from our model and the traditional conjoint model.

<Insert Table 14 about here>

As we can see in Table 15, our proposed model has a smaller DIC value as compared to the traditional model. According to Spiegelhalter, Best, Carlin, and Linde (2002), our model will make better predictions on consumer's purchase likelihood as compared to the traditional conjoint model. In addition, we compare the mean absolute error (MAE) between the actual individual-level purchase likelihood and the predicted individual-level purchase likelihood on the holdout sample. As we can see, the MAE calculated from our model is also smaller than the traditional conjoint. Finally, we compare the specifications of the optimal product design evolving from our model and the conjoint model (Table 15). As we can, based on our model, the optimal product design should adopt shape 3 instead of shape 2. Interesting, our model also indicates that the optimal product should be priced at $99 instead of $79. On average, this optimal product design has 81.36% of the purchase likelihood across all the respondents. In

contrast, our model predicts that the average purchase likelihood of the optimal product design identified by the traditional conjoint model is only at 72.13%.

<Insert Table 15 about here>

This difference in optimal product design indicates that, without considering the unobserved mediating effect of the subjective product characteristics, the traditional conjoint model may misidentify the optimal product design. When we define consumer's purchase likelihood as a function of only the objective product attributes, the traditional conjoint method may indicate that the optimal product design should adopt shape 2, because the estimated direct impact of shape 2 on purchase likelihood is more than shape 1 and shape 3. However, because product shape also affects consumer's perceptions on perceived power and perceived comfort, which in turn influence purchase likelihood, the true impact of different shapes on purchase likelihood may be either underestimated or overestimated. In our case, it results in a difference in the selection of the optimal product design. With regard to the difference in the selection of optimal price levels, our explanation is that, at the population level, the respondents may perceive a $99 power tool to be more powerful than a $79 power tool. In the traditional conjoint model with only direct relationship from price to purchase likelihood, the magnitude of the negative price impact is overestimated. This result is in line with the extant literature on the information role of price on buyers' quality judgments of the products (see, for example, Rao and Monroe 1989 and 1996). After including perceived power as one predictor for purchase likelihood, such overestimation is corrected and we observe $99 as the optimal product level.

In sum, our proposed model provides better in-sample fit and out-sample

prediction as compared to the traditional model. Our model also provides more diagnostic information for product designers. As a result, our proposed model will help eliminate the potential misidentification that the traditional conjoint model suffers from in the selection of optimal product design.

4.2 Study Two: Design of a Toothbrush

4.2.1 Study Design

The data for this study were collected from undergraduate marketing students in a large public university. This study was conducted to further validate our proposed method. We selected the toothbrush category for our research for the following three reasons. First, a toothbrush is a product used everyday by nearly everyone. The vast majority of the population is at least somewhat concerned about both dental hygiene, and the perceived level of comfort of their toothbrushes. Second, we believe that the large variety of toothbrushes that exist in the market is an indication of consumer heterogeneity among different toothbrush designs. Finally, we wanted to test if our model is able to outperform the traditional conjoint model with a relatively low-involvement product category. This would indicate that our model will have a great deal of managerial impact on the design of appealing new products in many future applications.

At the exploratory stage, we made several field visits to local grocery stores and pharmacies to collect various types of toothbrushes. We then conducted pretests to identify a set of objective product attributes that are considered most salient in users overall evaluation of a toothbrush. Based on this, we classified the specifications of these toothbrushes into different categories. As the output of this exercise, a complete list of the objective product attributes and attribute levels were defined for this study (see Table

16). Brand was not selected for the same reason as we discussed in the power tool study. Among the toothbrushes we collected in the filed, we selected 14 toothbrushes with various combinations of different attribute levels for our study. The evaluations on 12 toothbrushes were used for calibration and the evaluations on the last 2 toothbrushes were used for holdout validation. We calculated the D-efficiency of our toothbrush study design as 70.62, which we consider to be quite reasonable.

<Insert Table 16 about here>

In this study, we conducted the study under two experimental conditions. In condition 1, we designed a survey in Media Lab. Pictures of these 14 toothbrushes were taken to depict their bristle designs and grip designs. During the study, a picture of the toothbrush along with verbal descriptions on its price, softness of bristles, head size, and angle of head was displayed on the computer screen. One profile of the toothbrush was shown at a time. The respondents were asked to indicate their purchase likelihood for each toothbrush on a scale from 1 to 11, with 1 representing "definitely would not buy" and 11 representing "definitely would buy". Basically, these toothbrush specifications are identical to the ones we used in condition 2 of the study. The only difference is that, in condition 1, only pictures and verbal descriptions were shown and, in condition 2, the actual products were shown to the respondents.

The experimental setup in condition 2 is similar to our power tool study. We masked the brand name on the toothbrushes and attached a tag to each toothbrush indicating its price and the softness of bristles. The respondents were asked to imagine that they were shopping for a toothbrush in a retail store. If wish, they could touch and feel each toothbrush before they provided their likelihood of purchase for each

toothbrush product. In stage two, the respondents were asked to rate each toothbrush on whether they perceive it to be effective or comfortable to use. We use a 4-item measurement on a 7-point scale ranging from "strongly disagree" to "strongly agree" to measure perceived effectiveness (i.e. "I expect this toothbrush to work well"; "This expect this toothbrush to be very effective to clean my teeth"; "This toothbrush will perform better than an average toothbrush"; and "This toothbrush will do a good job in preventing tooth decay"). A 3-item measurement scale is used to measure perceived comfort (i.e. "I expect this toothbrush to be more comfortable than an average toothbrush"; "This toothbrush is difficult to use" (reverse coding); "The design of this toothbrush is awkward" (reverse coding). A pilot study with 140 observations across 10 respondents was conducted to assess the validity and reliability of the measurement scales. The discriminant validity of these scales was testified through confirmatory factor analysis. The Cronbach's alpha for perceived effectiveness is .937 and perceived comfort is .713.

In condition 1, we have 896 observations across 64 participants. In condition 2, we have 1176 observations across 84 participants.

In this study, we also assessed how well our model could predict actual choice behavior of the respondents. For both conditions, at the beginning of the study, we offered each respondent $5. We told the respondents that they had to use this money to purchase one of the five toothbrushes we presented to them. These toothbrushes represent a good variety of price levels, bristle designs etc. We masked the brand name on the toothbrushes and attached a tag to each toothbrush indicating its price and the softness of bristles. At the end of the study, we gave the respondents the toothbrushes they had

selected and the amount remaining from the $5 after their purchase.

4.2.2 Model Estimation Results

In this section, we first present the estimation results obtained from our proposed model. Following this, we present the estimation results from the reduced model using the same dataset. Next, we briefly discuss the estimation results of data collected from condition 1 (i.e. Media Lab survey). Finally, we conduct the comparison between our proposed model, the traditional conjoint model with actual toothbrushes, and the conjoint model with a combination of picture presentation and verbal descriptions.

We use a Hierarchical Bayesian Path Analysis model to estimate the full model. A schematic relationship of the paths is shown in Figure 5. The relationships between the objective product attributes and consumer's perception on the subjective product characteristics are established by two stepwise regressions. In each regression, consumer's perception is defined as the dependent variable and all the objective product attributes are initially included as predictors and some attributes are dropped out because they do not provide significant explanatory power. In this study, we have found that price does not have any significant impact on consumers' perceptions on whether a toothbrush is effectiveness or comfortable to use. Instead, price only has a direct impact on purchase likelihood. The stepwise regressions show that perceived effectiveness is a function of bristle design, head size, softness of bristles, and angle of head. And perceived comfort is jointly determined by bristle design and grip design.

<Insert Figure 5 about here>

We ran two parallel Monte Carlo Markov chains with random selected initials to assess the convergence of the Gibbs sampler. We monitored the on-screen display of the

traces from each chain for each parameter. For all three models we estimated for this study, 9,000 iterations from each chain were used as burn-in. The next 10,000 iterations from each chain were used to obtain the posterior means and standard deviations of the parameter estimates. A skip factor of 10 was chosen to compensate for the fact that successive draws of the posterior estimates may not be independent. Therefore, 2,000 draws were used to construct the posterior parameter estimates.

In Table 17, we provide the parameter estimates on perceived effectiveness for 5 randomly selected participants from our sample. As we can see, across respondents, there is a large amount of heterogeneity regarding which type of bristle design is perceived to be more effective than others. However, in general, plain bristle design is considered to be the least effective. Other attributes such as softness of bristles, head size, and angle of head seem to have various amounts of influence on perceived effectiveness for different respondents.

<Insert Table 17 about here>

In Table 18, the parameter estimates on perceived comfort for the same 5 participants were provided. Again, plain bristle design is perceived to be the least comfortable for most respondents. Similar to the pattern we found the power tool study, in a comparison of the parameter estimates for different bristle designs in Table 17 and Table 18, we found that, for some respondents, the bristle design that is considered to be the most effective is not necessarily deemed as the most comfortable to use (e.g. Subject #14 and Subject #36). Plain grip seems to be perceived as the least comfortable. Some respondents seem to be more comfortable with concave grip design without thumb grip than thumb grip. Others' preferences are quite the opposite.

<Insert Table 18 here>

In Table 19, we provide the estimation results on purchase likelihood for the full model. As we can see, price has a direct negative impact on purchase likelihood. Both perceived effectiveness and comfort appear to exert positive impact on purchase likelihood, with some respondents emphasize more on effectiveness while others on comfort.

<Insert Table 19 about here>

Next, we present the traditional conjoint model parameter estimates for the same 5 randomly chosen participants in Table 20. In Table 21, the parameter estimates from 5 randomly chosen participants from the condition 1 conjoint model (conducted in Media Lab) are presented.

<Insert Table 20 about here>

<Insert Table 21 about here>

Because condition 1 and condition 2 studies were conducted on different data sets, we could not directly compare the model DIC values across these conditions. Therefore, in Table 22, we only listed the DIC values for our proposed model and the traditional hierarchical Bayesian rating-based conjoint model conducted on the same data set. Again, we have found that the DIC value of our proposed model is smaller than the traditional conjoint model. In Table 22, we also compared the mean absolute errors (MAE) between the indicated individual-level actual purchase likelihood data and the model predicted purchase likelihoods on holdout samples across three models. We observed that our proposed model predicts the individual-level purchase likelihood data the best, followed by the conjoint model using actual products as presentation stimulus.

The model that performs the worst is the conjoint model conducted using a combination of picture and verbal descriptions. We also calculated the hit rates of the three models using the commonly used first choice rule (i.e. the respondent chooses the product with the highest overall utility) to predict the actual choice behavior of the respondents. We found that the hit rate of our model is 72.6%, followed by 65.3% for the conjoint model using actual products as presentation stimulus, and 59.4% for the conjoint model conducted using a combination of picture and verbal descriptions (see Table 22). Srinivasan, Lovejoy, and Beach (1997) have found in their study that product-based conjoint method performs better than concept-based conjoint method. Our study further confirms their findings. In addition, we have found that the Hierarchical Bayesian Path Analysis model that incorporates the impact of consumer perceptions on the subjective product characteristics performs even better than a product-based conjoint model.

<Insert Table 22 about here>

Finally, we compare the optimal designs predicted by the three models (Table 22). The optimal designs predicted by the three models vary in bristle designs and grip designs. This is quite intuitive because the bristle and grip design of a toothbrush exerts indirect influence on purchase likelihood through perceived effectiveness and comfort. The absence of such effect in the traditional conjoint model led to the selection of suboptimal product designs. All three models predict that the optimal product should have full size head, medium bristles, angled head, and be priced at $1.99. It is not surprising that optimal products that evolve from all three models are low priced. Because price does not have any impact on perceived effectiveness or comfort of the toothbrush, consumers are always more likely to buy a lower priced toothbrush, given

everything else being the same. However, if the product designer knows the production cost of these toothbrush designs, he/she should be able to use the estimated purchase likelihood data to calculate the most profitable toothbrush design, which is not necessarily the low priced one. In our study, the optimal product design selected by our proposed model has 81.25% of the purchase likelihood across all the respondents. In contrast, our model predicts that the average purchase likelihood of the optimal product design identified by the traditional conjoint model using actual products is at 74.16% and the purchase likelihood is 68.24% for the traditional conjoint model conducted in Media Lab.

<div align="center">5. Discussion and Conclusions</div>

Our research has developed a methodology to incorporate the impact of subjective product characteristics into the selection of optimal product designs. In many product categories, it is very essential to consider the role of consumer perception on the overall attractiveness for the product. This area of research has not received till date much attention in the new product development area. Hopefully our study can stimulate some interest on this important research topic.

We propose a Hierarchical Bayesian Path Analysis model to incorporate the impact of both the objective product attributes and subjective product characteristics into the estimation of individual-level consumer preference. Our proposed methodology moves beyond the existing literature in decomposing consumer preference solely as a function of the objective product attributes, and hence provides us with better understanding of consumer's product evaluation process.

Both studies in our empirical application indicate that consumers do use objective

product attributes as cues to make inference about the subjective characteristics of the product. Consistent with Huber and McCann (1982)'s findings, these unobservable subjective characteristics are integrated with the objective product attributes to exert a joint impact on consumer's preferences towards a product. As a result, the incorporation of these relationships in product evaluation can provide the product designer with better understanding and prediction on how to design optimal new products for the end users.

ESSAY 3: DESIGN OF ROBUST NEW PRODUCT UNDER VARIABILITY: MARKETING MEETS DESIGN

ABSTRACT

In designing consumer durables such as appliances and power tools, it is important to account for variations in product performance across different usage situations and conditions. Since the specific usage of the product and the usage conditions can vary, the resultant variations in product performance can also impact consumer preferences for the product. Therefore, any new product that is designed should be *robust* to these variations – both in product performances and consumer preferences. By a robust product design we are referring to a design that has (i) the best possible (engineering and market) performance under the worst case variations, and (ii) the least possible sensitivity in its performance under the variations. Achieving these robustness criteria, however, implies consideration of a large number of design criteria across multiple functions. In this paper, our objectives are (1) to provide a tutorial on how variations in product performance and consumer preferences can be incorporated in the generation and comparison of design alternatives, and (2) to apply a Multi-Objective Genetic Algorithm (MOGA) that incorporates multi-function criteria in order to identify good design candidates effectively and efficiently. The generation of design alternatives for prototype consideration will be accomplished using an iterative MOGA, which is used to search for better designs while incorporating the robustness criteria in the selection process. Since the robustness criteria is based on variations in engineering performance as well as consumer preferences, the identified designs are robust and optimal from different functional perspectives, a significant advantage over extant

approaches that do not consider robustness issues from multi-function perspectives. We believe our approach is particularly useful for product managers and product development teams, who are charged with developing prototypes. They may find the approach helpful for obtaining customers' buy-in as well as internal buy-in early on in the product development cycle, and thereby reducing the cost and time involved in developing prototypes.

We illustrate our approach and its usefulness using a case study application of prototype development for a hand-held power tool.

1. Introduction

It has been long recognized that successful New Product Development (NPD) involves effective integration of cross-functional processes. Extant research has shown that effective integration can have positive impact on product development cycle time (Griffin 1997; Sherman, Souder, and Jenssen 2000; Urban et al. 1997), project performance (Griffin and Hauser 1992; Olson et al. 2001), and overall company and market performance (Gemser and Leenders 2001; Griffin and Hauser 1996; Tatikonda and Montoya-Weiss 2001). Consequently, it is no surprise that the specifics of the cross-functional approaches that can lead to such successful impacts have been the focus of research in the last decade – Quality Function Deployment (QFD) ("house of quality") approach (Griffin 1992; Griffin and Hauser 1993; Hauser and Clausing 1988), lead user analysis (Urban and Von Hippel 1988), and integrating customer requirements into product designs (Bailetti and Litva 1995; Urban et al. 1997). The approach described in our paper belongs to the above genre of research, focusing on the development of specific methodologies to facilitate effective and efficient co-ordination between various functions in developing good candidates for prototypes.

The key characteristic of a cross-functional approach is that it necessarily entails consideration of a large number of factors that contribute to the design. Among these factors, some are specific and unique to individual functions and some are common across functions. Typically, many of these factors are interrelated and affect the design decisions that fall under the domain of the different functions. The power of a cross-functional approach cannot be harnessed unless all these factors and their interrelationships are systematically considered and accounted for in the design

development. Thus, an effective and efficient method for considering and integrating these factors is critical for reducing the time and cost of developing design prototypes. Our current study provides a tutorial on such a method in the context of consumer durable products. As compared to extant coordinating mechanisms, our approach has two distinguishing characteristics: first, we examine in detail how variations in product performance and consumer preferences, due to variations in operating conditions or otherwise, can be incorporated in the generation and comparison of design alternatives; second, we apply a multi-objective genetic algorithm that incorporates multi-function criteria in order to identify good design candidates. Our approach, thus, leads to the identification of "robust" design candidates for prototype development. We elaborate on these distinguishing characteristics in the following discussion.

Robustness of products is a critical element to consider in the new product development process, especially in the case of consumer durables such as appliances, power tools, utility vehicles. These products tend to be used in different usage situations and usage conditions in which their performance can vary depending on the operating conditions. For example, a truck could be used to transport goods ranging from sand to cartons, and used in different conditions depending on the geographical location and season. Similarly a power tool could be used in different applications such as concrete, wood or metal under operating conditions that could be very different depending on whether it is used in cold or hot weather. We use the term "parameters" to indicate such factors that can vary and are not under the control of the designer, e.g., different goods in the truck example; different applications or operating conditions in the power tool example. In this context, we define an optimal robust design as the one that satisfies the

following criteria: first, it has the best possible (engineering and market) performance under the worst case of uncontrollable parameters; second, it has the least possible sensitivity in its performance under variations in uncontrollable parameters.

From the engineering perspective, ignoring the variation in the performance of the products under various usage situations and conditions may lead to malfunctions of the product and can possibly cause serious failures (Kouvelis and Yu 1997; Parkinson, Sorensen, and Pourhassan 1993; Su and Renaud 1997; Sundaresan, Ishii, and Houser 1992; Zhu and Ting 2001). Therefore, engineering designers often aim to select designs that meet the following criteria: 1) maintain feasibility under variations (that is, the product still functions under variations), 2) show the least possible variation in its performance, and 3) have the best possible performance under the worst case variations in parameters. This renders *design robustness* a critical factor to consider in the new product development process.

From the marketing perspective, the variations in performance of the product under different usage situations and conditions can have a significant impact on customers' preferences for the product. Assume that these variations in performance can be mapped on to the levels of product attributes that customers typically consider in a preference elicitation process such as conjoint study. The marketing team can, then, estimate how changes in usage situations and conditions affect the preference rankings of customers for the alternative products and how robust the preference rankings for the alternative products are under such changes. This is one component of *preference robustness*. In addition, when customer preferences and part-worths for attributes are estimated using choice models, there are sampling errors associated with the estimation

procedure. In the literature of choice-based conjoint models, this issue of preference robustness has been virtually ignored. Marketing researchers have generally adopted the point estimates provided by the conjoint model, instead of recognizing the degree of error around the point estimates of consumer preferences. In order to account for the uncertainties in customer choices in the preference rankings, we can use the variances and co-variances of part-worth estimates from the choice model to construct interval estimates of conjoint utilities for each product alternative. When a set of competitive products is defined, the variation and the upper and lower limits associated with these interval estimates can provide a measure of how robust the preference rankings are under uncertainties associated with customer choices in a competitive setting. This is the second component of *preference robustness*. Thus, considering preference robustness in selecting the design for the new product can help in identifying designs that, hopefully, dominate other alternatives on the preference dimension given the variability in (1) usage situations and conditions and (2) customers' preferences estimates.

While our approach considers both design robustness and preference robustness in evolving new designs, the evolution process itself will be accomplished using Multi-Objective Genetic Algorithm (MOGA). Genetic Algorithm (GA) is based on the principles of natural selection ("survival of the fittest") in the evolution of species (Holland 1975). It has been successfully used in various applications including product design selection (Goldberg 1989; Holsapple et al. 1993; Narayanan and Azarm 1999). In marketing, Balakrishnan and Jacob (1996) proposed the use of single objective Genetic Algorithm (GA) to solve the problem of identifying an optimal (single) product using conjoint data. More recently, Steiner and Hruschka (2003) extended their approach by

applying single objective GA to solve for optimal product line design. Extending the work of Balakrishnan and Jacob (1996) and Steiner and Hruschka (2003), our approach applies GA to a multi-objective optimization problem with multiple constraints to account for robustness in both design and marketing. It also extends the single objective robustness criteria proposed by Kouvilis and Yu (1997) to the multi-objective robustness domain.

The preceding discussion highlights the contribution of our approach from an academic perspective. Our approach considers the variations in customer preferences for products due to variations in usage situations and conditions and due to estimation errors, which have been generally ignored in extant research. This variation along with variations in engineering performance are used in multi-objective genetic algorithm to identify robust prototype candidates, thus developing designs that are desirable from different functional perspectives, a significant advantage over extant approaches that do not consider robustness issues from multi-function perspectives.

From a practitioner viewpoint, we believe our approach is particularly useful for product managers and product development teams, who are charged with developing prototypes. They may find the approach helpful for obtaining customers' buy-in as well as internal buy-in early on in the product development cycle. We argue that having such an integration occur early on in the design process affords reduction in the cost and time for the selection of design alternatives because all design factors deemed important from the multiple functional perspectives are considered in a systematic and transparent manner in the prototype selection. This should enable quick buy-in from all functions involved in the design process.

The rest of the paper is organized as follows. In the next section we provide a brief description of the NPD case study and an overview of our approach. In the third section, we describe the design module. In the fourth section, we describe our preference elicitation module and process. In the fifth section, we describe our integrated multi-objective robustness criteria and the evolution of design alternative to carry forward to the prototype stage. We plan to illustrate our approach with a case example. The sixth section gives a brief description of how we plan to implement our approach. In the last section, we conclude with a discussion of the positive aspects of our approach and directions for future work.

2. Conceptual Framework

Our approach has been developed on the basis of an NPD project at a power tool manufacturer. We provide a description of the project to better motivate the approach we propose. The project involves a handheld power tool aimed at the industrial, professional and do-it-yourself markets. Two functional teams are closely involved in the development project: (1) design team, which selects the design inputs (such as motor type, gear ratio, and battery type) that affect tool design attributes such as power rating (performance), armature temperature (which determines life of motor/product), motor casing temperature, etc., and (2) marketing team, which researches and models customer needs, preferences and the competitive landscape to select the appropriate targeting, pricing and positioning strategies in consultation with the other functional teams. Since the product being designed will either be added to the existing product-line or replace an existing product, our approach is tailored for existing markets and we assume that customers have experience with similar products and will be able to evaluate product

features and trade-offs in reliable manner in a preference elicitation process.

Figure 6 shows our overall cross-functional framework for new product development. The framework assumes that initial exploratory studies have already been conducted by the product development teams consisting of marketing and design experts in understanding the general dimensions on which the new product could perform better compared to the competing products in the market. Such exploratory studies are based on laboratory research, field studies, and focus groups. These studies help the team to identify the important dimensions for marketing and engineering performance of the product. These dimensions form the basis for the design objectives, design attributes, marketing attributes and their levels to include in the customer preference/part-worth elicitation process.

<Insert Figure 6 about here>

Figure 6 is a bottom-up flow chart of our overall approach. There are two starting points in the framework. In the preference elicitation module (right-hand column in Figure 6), the most important customer needs with respect to the new product are first identified based on the exploratory studies. These customer needs can translate to levels in marketing attributes such as retail prices, brand name, life of product, power rating, switch type and actuator type. Once these attributes and their possible levels (values) are identified, a choice-based finite mixture conjoint analysis is used to estimate consumer preferences (or utilities) for different levels of attributes at market segment level, while accounting for the uncertainty in customer choices. The output of the preference elicitation module includes estimates of part-worths, the variance and co-variance of the estimates for each market segment, which can be used to construct preference rankings

and measure the preference robustness. These estimates are also useful to set up objectives and to construct constraints for the mutli-objective optimization problem.

In the design module (left-hand column in Figure 6), the engineering design team first identifies a set of design inputs that define the functional design of the new product. Examples of design inputs are motor type, battery type, gear ratios, gearbox type, etc. For each element of design input, there generally exist one or several design parameters. These design parameters are uncontrollable factors that can have a significant impact on the performance of the tool. For example, a design parameter associated with battery type is battery current. While the designer can assume a nominal (that is, the most likely) value for the current for each type of battery, the actual values of this parameter greatly depend on the usage conditions or situations. These design inputs are fed into a design simulation software. Each combination of the design inputs represents one design alternative. The design simulation software uses these inputs to generate design attributes which describe the performance or other features of the design corresponding to the set of inputs – for example, power rating, armature temperature (closely related to life of product), rotor speed, cost (closely related to retail price), etc. The actual values of these design attributes depend on the selection of design inputs and the specific values of the corresponding design parameters.

Some of the attributes considered in our framework are not only relevant for engineering of the product but they are also key attributes that consumers consider when he/she makes the purchase decision (e.g. price, power, life of the product, etc). Such product attributes are considered *common* to both marketing and engineering functions.

However, other product attributes are not common across all functions. For

example, attributes such as brand name or switch type are relevant only for marketing. These attributes are not very relevant to the engineering performance of the product. In our multi-objective optimization process, we only consider the uncertainties associated with customer choices as sources of preference robustness when calculating the interval estimate of market share for each design alternative.

More importantly, we incorporate the interval estimates of the part-worth utilities of the *common attributes* for the fitness assessment of integrated marketing and engineering robustness (the bold arrow linking the two columns at the top middle in Figure 6). The customer utilities for the attributes common to marketing and engineering functions are used in the design module in two ways. First, the utilities can help the designer to identify the appropriate objective functions or constraints in optimizing design performance, while accounting for design robustness. Second, the utility weights are used to construct measures of preference robustness under engineering variability, which along with design robustness measures, guide the evolution of optimal designs in the multi-objective optimization process. The output of the optimization process generates the set of "Customer-Based Robust Pareto" design alternatives. These design alternatives are chosen for prototype development, field performance evaluation and market simulations.

In the following sections, we provide the specifics of each module illustrating the process with examples from the case study.

3. Design Module

The design module focuses on the uncertainties in material and usage situations, application type and conditions (which we define as design parameters) that affect design

attributes such as power rating (performance), armature temperature (life of motor/product), motor casing temperature, and cost. While the goal of a deterministic optimization study is to design a product that reaches its optimum performance or a desired level of compromise between its design attributes (i.e. multi-objective optimization) under nominal values of the design parameters, in practical applications of the product, the design parameters often deviate from their nominal values (DeLaurentis and Mavris 2000). As a result of such deviations, the deterministic optimum design may show a significant degradation in its performance in the field, which can also affect customers' preferences for the product. Therefore, we take the uncertainties in the design parameters into consideration along with uncertainties in preference estimates in the robust optimization process.

Several researchers in engineering design have investigated the effect of variability in parameters for single-objective design optimization problems, e.g. (Badhrinath and Rao 1994; Chen and Yuan 1999; Parkinson, Sorensen, and Pourhassan 1993; Sundaresan, Ishii, and Houser 1992; Taguchi, Elsayed, and Hsiang 1989). Taguchi et al. (1989) define robustness as: "the state where the technology, product, or process performance is minimally sensitive to factors causing variability (either in manufacturing or in the user's environment) and aging". Parkinson et al. (1993) have categorized the robustness into two categories: *feasibility robustness* that refers to satisfaction of the design constraints despite parameter variations, and *sensitivity robustness* that refers to the reduction of the sensitivity of the design attributes.

In our approach, we extend the robustness definitions introduced by Kouvelis and Yu (1997) for single objective problems by considering the case of multiple objectives.

In our design robustness assessment, the goal is to identify superior design alternatives based on the following three selection criteria. *First*, the design should maintain feasibility with regard to design constraints under variations in design parameters. *Second*, the design should show the least possible variation in its design attributes. *Third*, the design should have the best possible performance in terms of the design attributes under the worst-case of the design parameters. In the following sub-sections, we provide detailed descriptions of each robustness criterion, that is, feasibility robustness and multi-objective robustness.

3.1 Feasibility Robustness

The goal of feasibility robustness is to ensure that the design will not violate design constraints for the worst case of uncontrollable parameters. Typically, a designer specifies a threshold value (called the "infeasibility threshold") on each important design attribute dimension. If, for a particular design alternative, the value of the design attribute exceeds this threshold level under the worst-case scenario, then the design candidate will be deemed "not feasibly robust". For example, the designer can specify that the armature temperature of the motor should not exceed $150^{o}F$ under the worst-case of the parameter values. This is because armature temperature plays a critical role in determining motor life and the life of the product, and exceeding this temperature may result in product failure. In this case, $150^{o}F$ is the infeasibility threshold on the armature temperature attribute, and if a design alternative generates an attribute value exceeding the threshold under this worst-case scenario, it will be eliminated. This criterion is fed into the multi-objective optimization problem to eliminate some of the inferior design candidates.

3.2 Multi-Objective Robustness

We will explain this criterion using an illustration. Consider a motor type (a design input) which impacts design attributes such as armature temperature and power rating. The values of these design attributes for a given motor type are affected by uncontrollable variations in design parameters such as motor current and ambient temperature. Even though for each type of motor, the designer can assume a nominal value for motor current and ambient temperature, the actual values of these design parameters depend greatly on the usage conditions or situations. Once a motor type is chosen by the designer, the variations in the design parameter space (motor current and ambient temperature) can be mapped onto the corresponding sensitivity region in the design attribute space (armature temperature and power rating) using a design simulation method (Roy, Parmee, and Purchase, 1996) (see Figure 7, where the nominal point and sensitivity region are shown).

<Insert Figure 7 about here>

Given a design attribute space, the designer can typically specify a target point that a design alternative should aim for in its design attribute values. This target point becomes the basis for determining the worst-case attribute values and the best-case attribute values under the variations in the design parameters. We define multi-objective variability in design attributes as the distance between the worst-case point and best-case point, as shown in Figure 7.

Our criterion of multi-objective robustness implies the following in comparing two design alternatives from the engineering domain: (i) the closer the worst-case point is to the target point, the better the design, and (ii) the lower the multi-objective variability, the better the design. Figure 8 displays two design alternatives A and B with their

sensitivity regions, nominal points, worst-case points, and best-case points. While in the nominal case design A outperforms design B in the attribute space, in the worst case, design B is better than design A. In addition, design B exhibits a lower variability than design A. Accordingly, design B is multi-objectively more robust than design A from the engineering domain. If a design alternative does not perform better compared to another on both (i) and (ii), then the designs are referred to as non-dominated with respect to each other.

< Insert Figure 8 about here>

4. Preference Elicitation Module

We use choice-based conjoint methodology for customer preference elicitation. Conjoint analysis has been a major tool in the process of product design for the last two decades (Green and Srinivasan 1990; Carroll and Green 1995). In a typical conjoint-based product design procedure, consumers' preferences are estimated through an evaluation of a set of hypothetical product profiles that are specified in terms of levels of different attributes. Estimated part-worth utilities are used to calculate the potential market shares of the proposed product concepts against existing competitors' products.

In our conjoint choice experiment, respondents are asked to express their preferences by choosing product profiles in each conjoint task. A finite mixture multinomial logit model is used to identify the number of segments in the market (Kamakura and Russell 1989; Vriens, Wedel, and Wilms 1996).

A choice model for a conjoint choice experiment starts with J individuals, each evaluating K different sets of products (called choice sets). Each of the K choice sets contains M product profiles. A customer chooses a profile from each of the K choice sets

based on his preference for the products. If we assume the existence of $s = 1,…,S$ segments with segment size SS_s, the utility of an individual c for profile m in choice set k, given that this individual belongs to segment s, is defined as follows:

$$u_{cs}(\mathbf{y}_{mk}, P_{mk}) = (\mathbf{y}_{mk}\boldsymbol{\beta}_{sy} + P_{mk}\boldsymbol{\beta}_{sp}) + \varepsilon_{csmk} \qquad (1)$$

Where $\mathbf{y}_{mk}$ is a $\alpha\times1$ vector representing product attributes of product alternative m in choice set k and P_{mk} is price of product in choice set k and $\boldsymbol{\beta}_{sy}$ is a $\alpha\times1$ vector of parameter coefficients weighting each product attribute levels, $\boldsymbol{\beta}_{sp}$ is a vector of parameter coefficients for prices, and ε_{mk} is a random component of the utility. In our example, all product attributes are coded as dummy variables. Therefore, $\mathbf{y}_{mk}$ is a $\alpha\times1$ vector of zeros and ones with ones representing the corresponding product attribute levels of product m. Because of the linear dependency nature of these dummy variables within each product attribute, in order for this model to be identified, we omit one level for each attribute in the estimation and a value that is equal to the negative of the sum of the utility estimates of all other levels is used as the utility for the missing level.

If we assume that the random component ε_{csmk} follows an independent identical double exponential distribution, the probability that product m is chosen from choice set k, conditioning on consumer c being a member of segment s, can be expressed as follows:

$$\Pr_{cmks} = \frac{\exp(\mathbf{y}_{mk}\boldsymbol{\beta}_{sy} + P_{mk}\boldsymbol{\beta}_{sp})}{\sum_{mm=1}^{M}\exp(\mathbf{y}_{mmk}\boldsymbol{\beta}_{sy} + P_{mmk}\boldsymbol{\beta}_{sp}) + \exp(cons_s)} \qquad (2)$$

Where $cons_s$ represents the constant term representing the utility of the "no-choice" option for consumers in segment s.

Because SS_s represents the likelihood of finding a consumer in segment s, the unconditional probability of choosing product m from choice set k by consumer c can be computed as:

$$\text{Pr}_{cmk} = \sum_{s=1}^{S} SS_s \, \text{Pr}_{cmks} \qquad (3)$$

The probability of membership in a particular segment s is obtained by updating in a Bayesian fashion the prior probability of membership SS_s using the observed choice from a sample of consumers as a conditioning event. And the log-likelihood function is the sum of the log-likelihood functions of all choice sets for all consumers:

$$LL = \sum_{c=1}^{C} \sum_{m=1}^{M} \sum_{k=1}^{K} \ln(\text{Pr}_{cmk}) \qquad (4)$$

Using maximum likelihood estimation method on equation (4), we are able to estimate segment-level conjoint utilities. Akaike's information criterion (*AIC*) is used to specify the number of segments in the market to avoid overfitting the data .

$$AIC = -\frac{2(LL - q)}{SS} \qquad (5)$$

Where *LL* is the log likelihood total, q is the number of parameters to be estimated, and *SS* is sample size.

As we can see, the outputs of the finite mixture conjoint estimation provide a set of part-worths for all the attribute levels for each segment. The use of such estimation methods allows us to understand the preferences of different market segments. And we can use the estimated segment-level part-worths to predict market share of each hypothesized product design given a set of competitors.

More importantly, in the context of our focus on robust selection, the

methodology takes into account the uncertainty in customers' choice that could arise due to different factors. The error term in the utility equations of the logit model can be regarded as capturing the effects of omitted attributes, the effects of usage situations and conditions not accounted for in the design process, and any other variation not captured in the model. The finite mixture conjoint model provides us with estimates of the asymptotically robust variance and co-variance matrix of the part-worth estimates for each segment. Since these part-worth estimates are considered asymptotically normal (Ben-Akiva and Lerman 1985), we can construct the interval estimates of the part-worths for various design alternatives considered in the design process. In particular, for continuous product attributes such as power rating, we use the standard procedure of pair-wise linear interpolation (*Sawtooth Choice-Based Conjoint User Manual, Appendix C, 2001*) to calculate the point estimate and the lower and upper bounds of the 95% simultaneous confidence levels for utilities of power ratings that are in-between levels (Figure 8). By adopting the interval estimates of the conjoint utility in our model, we recognize one component of the preference robustness, which accounts for the uncertainties in customer choices in the preference ranking process.

< Insert Figure 8 about here>

Another component of the preference robustness in our model comes from the variation in the performance of the product from the engineering domain. For example, when the tool is used for different usage situations and under different conditions, the actual power rating of the tool may vary ±.5 amps from the nominal value. This variation will also have impact on consumer's preferences for the tool. In our model, we also attempt to account for the impact of such variation on the consumer's preference for the

product. As we can see in Figure 8, the upper and lower bounds of the conjoint utility for one nominal value of power rating are constructed in such a way that both components of the preference robustness are recognized.

On the basis of a pre-defined set of competitive products for the new product, we can estimate whether an alternative dominates (in a statistical sense) another alternative in terms of their predicted market shares using the estimated conjoint utilities, the associated asymptotical variance and co-variance matrix, and the estimated segment size. Namely, to be able to decide on the statistical dominance, the interval estimates of market shares for the alternatives should not have any overlap. In other words, alternative A provides a significantly higher market share than alternative B if and only if the lower bound of alternative A's market share interval estimate is greater than the upper bound of alternative B's market share interval estimate. These interval estimates are used as the measure of preference robustness. They are combined with the design robustness measures to collectively determine the final robust design set. More details about our integrated robust approach are provided in the next section.

5. Integrated Robustness Assessment Using MOGA

In search for the final set of robust design alternatives for the prototypes, we integrate the design robustness and the preference robustness criteria using an adaptive search technique called Multi-Objective Genetic Algorithm (MOGA). MOGA is a multi-objective optimization method that is able to handle both discrete and continuous design inputs and parameters, as is the case in the problem under consideration (for instance, gear ratio is a continuous variable while motor type is a discrete variable). This technique requires the representation of each design alternative in a binary string format. In the

context of our study, each design alternative or "chromosome" is composed of several concatenated strings (design inputs and product features that define the design alternative). Each string is made up of binary sub-string positions with each sub-string corresponding to the specific level of each design input or product feature. If one sub-string has a length of k, GA can store up to $(2^k - 1)$ different levels (exclude level zero) in the sub-string. For example, if a design could have any one of the four possible switch types and one of the two possible types of actuators, its chromosome representation could be "100 01", which corresponds to the 4th switch type (i.e. $0 \times 2^0 + 0 \times 2^1 + 1 \times 2^2 = 4$) and the 1st type of actuator (i.e. $1 \times 2^0 + 0 \times 2^1 = 1$). For continuous design inputs such as gear ratio the string presentation is illustrated by the following example - a gear ratio of 5.3 is represented as "0101 0011", since $1 \times 2^0 + 0 \times 2^1 + 1 \times 2^2 + 0 \times 2^3 = 5$ and $1 \times 2^0 + 1 \times 2^1 + 0 \times 2^2 + 0 \times 2^3 = 3$.

The schematic in Figure 10 provides an overview of how multi-objective robustness, feasibility robustness and preference robustness are considered in the application of MOGA (Coello, Veldhuizen, and Lamont 2002; Deb 2001). The process begins with the decision maker specifying the infeasibility thresholds on different dimensions and the target points in the attribute space. The target points are used to normalize the objective and constraint function values so that they are of the same order of magnitude. Next, an initial random set of design alternatives is generated. Each design alternative selected from this set goes through the feasibility robustness assessment. If the design alternative satisfies the feasibility threshold requirement, it becomes a potential design candidate for multi-objective robustness assessment and optimization.

<Insert Figure 10 about here>

In developing the fitness assignments for each design candidate which is essential for pruning the set of alternatives, the optimizer solves for the worst-case values and the variability measurement in engineering design attributes. The variability in attribute values for attributes common between the preference elicitation module and the design module are also used to determine the corresponding interval estimate of the market share of each design candidate when performing the preference robustness assessment. The multi-objective optimization technique guides the search based on the multi-objective ranking of design robustness and preference robustness (Zenios 1995). The integrated design and preference robustness assessment is based on the criterion that, given two design alternatives A and B, alternative A is preferred to B if and only if A is superior in both design and preference robustness assessments.

The search continues, until a MOGA's stopping criterion is met. (A typical stopping criterion is to stop the algorithm when the fitness of design alternatives in the population over several generations is unchanged.) If the stopping criteria are not satisfied, three operators are used to create the next generation of design alternatives. These three operators are: 1) reproduction, wherein a subset of the alternatives are chosen based on their fitness and copies of their profiles are generated; 2) crossover, wherein pairs of design alternatives are chosen and, along specific positions on the strings, genetic material between the two strings are exchanged leading to offspring (i.e. two new design alternatives); and 3) mutation, wherein a design alternative is randomly chosen from the population and the binary value at a specific location (design input and product feature) in the string is modified. At the end of each iteration, the stopping criteria are checked and the iteration continues until the optimizer's stopping criteria are met.

The result of the application of MOGA is a set of robust Pareto solutions that are non-dominated by any other alternative considering both the design objectives and the marketing objective (see Figure 11). It should be noted that if we apply MOGA without considering the customer preferences, it would still provide us with solutions in the Pareto frontier, albeit in the context of only the design objective functions that we consider. When we consider customer preference and preference robustness in MOGA then we obtain solutions in Pareto frontier that have higher marketing performance as well as contain solutions that a MOGA without preference robustness considerations may not have generated. In theory, both approaches should provide designs that are on the Pareto frontier. However, in a practical application, by considering customer preferences and preference robustness in our approach we should be able to identify designs in the Pareto frontier that have potential higher marketing performance as compared to the case of MOGA without considering preference robustness.

<Insert Figure 11 about here>

6. Case Study Application

In this section, we describe the application of our approach to the power tool development project. Based on exploratory research and internal discussions, the marketing and design teams chose the following product features: brand, price, power rating, life of product, switch type, and actuator type. The switch attribute consisted of four levels – three switches that already existed in the market and a new switch that the ergonomic team had designed. There were two types of power actuators (A and B). Four different brands were considered, along with three levels of price, three levels of power rating and three levels of life of product.

Respondents for the study included metal workers and construction workers (who make up 80% of the user base for the tool) recruited from job sites and construction sites. The interviews were conducted with 249 respondents from different markets, each interview lasting around 25 minutes. Each respondent was given 18 choice scenarios (16 were used for conjoint estimations and 2 were used for validation). One respondent didn't complete the conjoint study and his responses were excluded from our data analysis. We generated the choice scenarios using the procedure described in Huber and Zwerina (1996). Each choice occasion included two alternative designs and a no-choice option. Respondents were asked to consider different usage situations when making their choices. The data was collected and estimated using Sawtooth Latent Class Module. Table 23 provides the part-worth estimates associated with each attribute level and the utility estimate for "no-choice" in each market segment. In this table, we also provided the values of the segment sizes[11].

<Insert Table 23 about here>

The set of design variables are: choice of motor (x_m) which is a discrete variable between 1 to 10, choice of speed reduction unit or gearbox (x_g), a discrete variable between 1 and 6, the gear ratio (x_r) which is a continuous variable between 3.5 and 5.0. There are 5 design parameters that affect the performance of each design alternative. The design parameters' information is given at Table 24.

<Insert Table 24 about here>

To ensure performance and efficiency of the product and reduce the effects of vibration to the user, the engineering design objectives are defined as follows. The

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[11] To save space, the variance and co-variance matrix for each market segment is not displayed here. They

product's output motor speed is minimized while the amount (i.e., mass) of material removed maximized. To guarantee that the product does not fail (i.e., burn out) under demanding application conditions, a design constraint is imposed to keep the motor temperature (which is the larger of armature temperature and field temperature) less than 220°C. These engineering design objectives are common between design module and the preference elicitation module (see Figure 6). Amp rating is obtained using maximum motor output power. Based on product testing in laboratory studies, the relationship between armature temperature and life of product was determined by the design team, and was incorporated in integrating the robustness measures[12]. Similarly, cost of the design and price of the product (which are common between the two modules) are related using manufacturer margin goals[13].

Given these two objectives and constraint, without considering the effects of parameter variations on them, a multi-objective genetic algorithm (MOGA) optimization method is used to obtain the set of customer-based Pareto designs. The parameters used for MOGA are given in Table 25.

<Insert Table 25 about here>

There are many constraints for this optimization problem, but we highlight a few that are relevant for the objectives considered. The price of the new product was restricted to under $180, which in turn implied a cost constraint in the design module and had impact on the various combinations of design inputs that had to be restricted (for

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can be obtained from the authors.

[12] This relationship has also been simplified for expositional purposes.

[13] We have computed price as cost plus manufacturer margin plus retailer margin. In actual practice, the price is determined by the marketplace, but goals regarding manufacturer margin is a significant input to this process.

example, the more expensive component combinations were restricted).

The multi-objective optimization using genetic algorithm works as follows:

Step 1: Initial Population Generation: We pick 100 design alternatives at random to be evaluated by specifying motor type, battery type, and gear ratio. For each alternative we define all combinations of the parameter space (motor current, ambient temperature, battery current and battery voltage, in our case). Using design simulation, we can evaluate the performance of these designs (in our case, the two objectives of armature temperature and power rating) under varying conditions of parameter values for each design alternative.

Step 2: Feasibility Robustness: We evaluate the feasibility robustness of each design alternative taking the infeasibility thresholds into account. Those designs exceeding the infeasibility threshold are eliminated from further consideration.

Step 3: Integrated Robustness Assessment: We combine preference robustness along with design robustness to identify non-dominated designs. For the successful candidates that remain (i.e. those that pass the feasibility requirements), the sensitivity region for each design alternative will be formed. Using the approach described in the Design Module Section, the worst-case point distance from the target point and multi-objective variability are calculated for every design alternative. Using the approach described in Preference Elicitation Module Section, we calculate the interval estimate of market share for each design alternative as the measure for preference robustness. The designs are deemed to be robust are retained.

Step 4: Check Stopping Criteria: We employ a moving average rule as our stopping criterion (Balakrishnan and Jacob 1996; Steiner and Hruschka 2003). Namely, if the

average fitness of the best strings of the current generation has increased by less than a small percentage as compared to the average fitness of the best strings from a few previous generations, then we stop with the identified best designs. If the stopping criteria for the optimization are not met, the best designs arising from Step 3 will be retained for the next step of the genetic algorithm for crossover and mutation.

In our application to the organization's problem, the integrated robustness assessment process using MOGA leads to the identification of 62 product alternatives as the best robust designs from both marketing and design perspectives. Even though it may not be feasible to carry forward all 62 products to prototyping stage, our proposed methodology provides an avenue for the design team to reduce the number of design alternatives from infinite to a manageable number in an efficient and effective way. There are many methods to make a selection among the generated alternatives. For instance, the producer can develop some of these designs further into prototypes and conduct additional performance evaluation in the field to select the final product for mass-production. Also, the managers can make a selection decision based upon the market positions of competitive products to maximize the new product's differential competitive advantage. Finally, the optimal product can be chosen based on the long-term profit it will create after the design and marketing robustness under different usage situations and conditions are accounted for. For example, the life-cycle product cost-benefit analysis proposed by Ramdas and Sawhney (2001) can be used to map out the most profitable product based on the combination of production cost and life-cycle operating cost incurred over the product's life cycle. The issue of product design selection is beyond the scope of this publication. Hence we do not provide detailed

discussion here.

7. Conclusions

In this paper we have proposed an approach that focuses on the issue of robustness from design and marketing perspectives. In product categories such as consumer durables, which are used under different conditions and for different applications, it is very essential to consider the impact of such variations on performance and customer preference (and market share or profit). This is an area of research that has not received much attention in the NPD literature and hopefully our study will stimulate some interest.

In an environment where most of NPD work is carried out in cross-functional teams, it is very necessary to have coordination processes that are efficient and effective to harness the power of such teams. The number of design inputs, attributes and parameters that are considered are typically very large and they tend to be interrelated and common across many functions. Our approach provides a clear, systematic method to consider these factors and integrate them in identifying good design alternatives. The approach is transparent. Thus, every functional team knows exactly how the factors it deems important relates with other factors that other functions consider important, and how each factor contributes to in identifying the designs for prototypes. This transparency enables quick internal buy-in within the teams for the chosen alternatives. Overall, this approach has a significant potential to reduce the cost and time of developing prototypes. It also enables the process to be market-focused early on in the product development cycle, as customer preferences are already accounted for at the prototype stage.

From an academic viewpoint, we propose a methodology that integrates issues of design robustness with those of customer preference robustness in evolving new design alternatives using multi-objective genetic algorithms. While the ultimate validation of our approach may be difficult to assess at this stage (and is a topic worthy of future work), it is quite evident that consideration of part-worth of attribute levels and customer utilities for product alternatives in the design stage can lead to a market-focused design evolution process. If the application of our approach results in the generation of a design with higher customer utility (and market share) that is discarded when the MOGA is repeated without considering customer utilities, we will be able to confirm one common adage in new product development – the design that has the best engineering performance may not be the one that is most preferred by the customer.

A significant advantage of our approach is that it is flexible enough to accommodate alternative measures in assessing customer preference robustness. We have used market share variations as our measure of preference robustness, but this could easily be converted to manufacturer profits. Since each set of design inputs can be associated with a cost attribute, manufacturer margin on each unit sold (retail price minus retail margin minus cost) can be determined for each design alternative. Thus, interval estimates for market shares can be converted to interval estimates for manufacturer profits for each alternative[14], and this measure can be used for robustness assessment of market profitability. In some instances, manufacturers may specify a retail price point that they target for a new product (This is quite common in the case study as retailers generally specify the price point they are looking for). In such a situation, one could fix

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[14] Manufacturer Profit = Market Share × Total Market in No. of Units × Manufacturer Margin per unit.

the retail price targeted and use manufacturer profit as a robustness criterion and as an

objective in the multi-objective optimization for evaluating alternatives rather than using

market share estimates.

TABLES

Table 1: Positioning Against Related Research

	New Product Entry	Individual-level Consumer Preferences	Retailer-Manufacturer Interaction	Manufacturer-Manufacturer Interaction
Villas-Boas (1998)	√		√	
Sudhir (2001)			√	√
Villas-Boas and Zhao (2005)			√	√
Horsky and Nelson (1992)	√			√
Kadiyali (1996)	√			√
This paper	√	√	√	√

Table 2: Estimation Results of Hierarchical Bayesian Conjoint Model

Parameter	Subj.#3	Subj.#36	Subj.#58	Subj.#97	Subj.#123
Brand A	2.774	.289	1.461	1.207	2.683
	(1.608)	(.945)	(1.127)	(1.342)	(1.177)
Brand B	-1.947	-1.343	.696	-2.240	-1.583
	(1.741)	(1.091)	(.781)	(1.141)	(1.256)
Brand C	-2.927	-.058	-4.082	-.769	-3.044
	(2.674)	(2.021)	(1.092)	(1.915)	(2.398)
Own Brand	2.100	1.112	1.925	1.801	1.944
	(2.170)	(1.470)	(1.698)	(1.613)	(1.479)
Price	-.342	-.010	-.224	-.170	-.354
	(.110)	(.054)	(.073)	(.078)	(.100)
Amp Rating(6)	-.328	-.736	-2.910	-1.253	-.024
	(1.179)	(1.165)	(1.043)	(1.063)	(1.129)
Amp Rating(9)	.073	.767	-.625	-.265	.095
	(1.144)	(.815)	(.879)	(1.069)	(.968)
Amp Rating(12)	.254	-.031	3.534	1.519	-.071
	(1.533)	(1.286)	(1.262)	(1.260)	(1.263)
Life of Product (80 hours)	-7.851	-1.224	-2.523	-4.297	-8.055
	(2.490)	(1.321)	(1.191)	(1.843)	(2.133)
Life of Product (120 hours)	3.165	-3.218	-.739	1.258	2.966
	(1.845)	(1.326)	(1.011)	(1.276)	(1.631)
Life of Product (150 hours)	4.685	4.443	3.262	3.039	5.089
	(1.475)	(1.190)	(1.031)	(1.265)	(1.309)
Paddle Switch	2.116	-7.995	-3.618	5.876	2.374
	(2.717)	(2.569)	(1.499)	(2.588)	(2.318)
Top Slider Switch	4.272	-4.480	-5.003	2.373	4.497
	(2.047)	(1.708)	(1.710)	(1.693)	(1.908)
Side Slider Switch	-6.614	-1.960	2.142	-5.326	-6.707
	(3.070)	(2.197)	(1.402)	(2.769)	(2.668)
Trigger Switch	.225	14.435	6.478	-2.922	-.164
	(4.087)	(4.562)	(2.311)	(4.201)	(3.829)
Actuator A	.531	2.345	-.086	5.775	.371
	(1.272)	(1.332)	(.797)	(2.142)	(.984)
Actuator B	-.531	-2.345	.086	-5.775	-.371
	(1.272)	(1.332)	(.797)	(2.142)	(.984)
No-Choice	2.585	-.184	4.311	11.267	2.554
	(1.943)	(1.501)	(1.229)	(3.001)	(1.554)

a.   Posterior standard deviation is in parentheses
b.   Log-likelihood: -1369.961
c.   Chi-Square: 6070.116
d.   Pseudo R^2: .690

Table 3: Consumer Choice Validation

		Predicted Share by Conjoint Utilities	Actual Share Indicated by Subjects
Holdout 1	Product 1	42.73%	34.14%
	Product 2	32.52%	35.34%
	No-Choice	24.75%	30.52%
Holdout 2	Product 3	15.29%	10.44%
	Product 4	30.70%	40.16%
	No-Choice	54.01%	49.40%

Table 4: Specifications of Competitive Products

Product	Brand	Price	Amp Rating	Product Life	Switch Type	Actuator Type
X	Brand A	$99	9	120 hours	Side Slider	Actuator B
Y	Brand B	$129	12	150 hours	Paddle	Actuator A
Z	Brand C	$79	6	80 hours	Paddle	Actuator A

Table 5: Estimated and Observed Market Shares of Competitive Products

Products	Estimated Market Share	Estimated Market Share(w/o No-Choice)	Observed Market Share
Product X	14.18%	18.88%	11.80%
Product Y	20.66%	27.51%	30.10%
Product Z	40.26%	53.61%	58.10%
No-Choice	24.90%	N/A	N/A

Table 6: Market Specifics – Before New Product Entry

		Product X	Product Y	Product Z
Model Estimates				
Retailer Estimates	Wholesale Price ($)	78.01	109.67	57.81
	Retail Margin ($)	20.99	19.33	21.19
Manufacturer Estimates	Marginal Cost of Production ($)	70.74	103.62	51.08
	Wholesale Margin ($)	7.27	6.05	6.73
Industrial Partner Estimates	Retail Margin ($)	23	21	22.5
	Marginal Cost of Production ($)	68.15	100.94	49.58
Market Size (units of potential purchase in millions)		9		
Marginal Shelf Cost ($ in millions)		26.4		
Retailer Category Profit ($ in millions)		60.31		

Table 7: Market Scenario Analysis – With Introduction of the New Product

Alt.#	Marginal Cost ($)	Equilibrium Retail Prices ($)				Equilibrium Wholesale Prices ($)				Status
		X	Y	Z	New	X	Y	Z	New	
3	77.14	96.68	128.91	78.85	103.18	78.54	109.67	56.70	86.25	X
7	105.79	97.48	130.16	79.75	131.60	78.46	109.95	56.46	113.87	X
10	54.73	100.36	132.88	82.35	81.65	78.04	109.10	54.77	60.92	√
16	83.85	100.05	134.96	89.73	116.56	72.98	106.05	56.01	91.54	√
29	85.76	98.99	133.09	81.02	111.32	77.65	110.40	54.96	91.48	X
Retail Prices (before entry)		99.00	129.00	79.00		78.01	109.67	57.81	Wholesale Prices (before entry)	

Table 8: Market Scenario Analysis: Replacing One Existing Product with Alt. # 10

Product Assortment	Equilibrium Retail Prices ($)			Equilibrium Wholesale Prices ($)		
{X, Y, New}	98.44	130.77	80.29	78.67	109.75	61.85
{X, Z, New}	94.16	76.28	76.54	79.59	58.75	62.85
{Y, Z, New}	127.82	77.61	78.14	110.04	57.25	62.45

Table 9: The Simultaneous-Move Game

		Manufacturer of Product X	
		Side Slider	Top Slider
Manufacturer of New Product	Top Slider	8.997, 8.118	7.349, 7.434*
	Side Slider	3.759, 8.166*	4.302, 9.250*

*predicted to be rejected by the retailer

Table 10: Objective Product Attributes and Levels for Power Tool Study

Attribute 1: Price
$79
$99
$129
Attribute 2: Weight
Light
Heavy
Attribute 3: Shape
Shape 1: Rear Motor
Shape 2: Ultimate Body Grip
Shape 3: Larger than UBG
Attribute 4: Switch
Switch 1: Top Slider
Switch 2: Side Slider
Switch 3: Paddle
Switch 4: Trigger

Table 11: Parameter Estimates on Perceived Power from the Proposed Model

	Perceived Power				
Parameter	Subj.#2	Subj.#9	Subj.#18	Subj.#31	Subj.#46
Constant	5.804	4.209	5.273	5.398	5.136
	(.472)	(.439)	(.460)	(.435)	(.388)
Shape 1	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Shape 2	.134	-.347	-.021	.031	-.258
	(.450)	(.399)	(.388)	(.299)	(.350)
Shape 3	.389	-.335	.158	.232	-.207
	(.379)	(.345)	(.135)	(.321)	(.274)
Light Weight	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Heavy Weight	.263	.363	.289	.235	.304
	(.361)	(.339)	(.304)	(.317)	(.269)
Price ($79)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($99)	.047	.365	.162	.012	.161
	(.078)	(.409)	(.101)	(.004)	(.027)
Price ($129)	.131	.404	.189	.030	.245
	(.122)	(.372)	(.221)	(.012)	(.295)

Posterior standard deviations are in parentheses

Table 12: Parameter Estimates on Perceived Comfort from the Proposed Model

Parameter	Subj.#2	Subj.#9	Subj.#18	Subj.#31	Subj.#46
	Perceived Comfort				
Constant	4.849	4.595	4.970	4.853	4.622
	(.374)	(.337)	(.376)	(.373)	(.337)
Shape 1	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Shape 2	.142	-.045	.117	-.213	-.083
	(.346)	(.333)	(.356)	(.357)	(.338)
Shape 3	.215	-.106	-.105	.108	.147
	(.332)	(.323)	(.363)	(.337)	(.321)
Top Slider Switch	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Side Slider Switch	.069	-.038	1.026	.062	-.122
	(.024)	(.288)	(.494)	(.312)	(.293)
Paddle Switch	.621	.527	.078	.550	1.069
	(.323)	(.305)	(.314)	(.318)	(.448)
Trigger Switch	.996	1.037	.576	.965	.515
	(.491)	(.429)	(.340)	(.497)	(.298)
Light Weight	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Heavy Weight	-.099	-.090	-.141	-.163	-.123
	(.280)	(.257)	(.299)	(.290)	(.281)

Posterior standard deviations are in parentheses

Table 13: Parameter Estimates on Purchase Likelihood from the Proposed Model

	Purchase Likelihood				
Parameter	Subj.#2	Subj.#9	Subj.#18	Subj.#31	Subj.#46
Constant	-2.498	-2.469	-2.514	-2.032	-2.461
	(.414)	(.426)	(.489)	(.426)	(.414)
Shape 1	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Shape 2	-.070	-.109	.219	-.150	.255
	(.342)	(.347)	(.340)	(.356)	(.348)
Shape 3	.326	.301	-.064	.277	.265
	(.289)	(.284)	(.285)	(.291)	(.280)
Top Slider Switch	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Side Slider Switch	.122	.123	.636	.117	.159
	(.271)	(.278)	(.510)	(.278)	(.272)
Paddle Switch	.338	.353	.116	.263	.663
	(.303)	(.327)	(.269)	(.319)	(.506)
Trigger Switch	.703	.682	.351	.657	.374
	(.497)	(.506)	(.313)	(.514)	(.320)
Light Weight	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Heavy Weight	-.228	-.247	.-227	-.318	-.229
	(.286)	(.292)	(.289)	(.287)	(.288)
Price ($79)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($99)	-.041	-.087	.070	-.002	-.014
	(.353)	(.351)	(.035)	(.359)	(.318)
Price ($129)	-.204	-.032	.118	-.066	-.241
	(.323)	(.323)	(.326)	(.359)	(.352)
Perceived Power	.073	.162	.121	.065	.135
	(.131)	(.153)	(.155)	(.153)	(.142)
Perceived Comfort	.446	.432	.454	.401	.412
	(.145)	(.147)	(.157)	(.156)	(.151)

Posterior standard deviations are in parentheses

Table 14: Parameter Estimates on Purchase Likelihood from Conjoint Model

	Purchase Likelihood				
Parameter	Subj.#2	Subj.#9	Subj.#18	Subj.#31	Subj.#46
Constant	-.164	.217	-.002	-.269	-.107
	(.422)	(.408)	(.447)	(.432)	(.409)
Shape 1	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Shape 2	.123	.272	.143	-.067	.349
	(.353)	(.362)	(.381)	(.379)	(.351)
Shape 3	.499	.301	.103	.152	.221
	(.327)	(.320)	(.338)	(.141)	(.317)
Top Slider Switch	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Side Slider Switch	.252	.039	1.221	.251	.114
	(.306)	(.201)	(.569)	(.400)	(.293)
Paddle Switch	.655	.661	.119	.494	1.239
	(.328)	(.332)	(.385)	(.361)	(.526)
Trigger Switch	1.214	1.240	.717	1.171	.696
	(.529)	(.531)	(.358)	(.559)	(.325)
Light Weight	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Heavy Weight	-.259	-.298	-.189	-.422	-.206
	(.317)	(.319)	(.359)	(.328)	(.305)
Price ($79)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($99)	-.088	.009	.166	-.007	-.071
	(.377)	(.379)	(.385)	(.395)	(.375)
Price ($129)	-.216	.002	.256	-.131	-.319
	(.388)	(.375)	(.381)	(.401)	(.338)

Posterior standard deviations are in parentheses

Table 15: Comparison between Proposed Model and Conjoint Model

	Proposed Model	Conjoint Model
In-Sample Fit (DIC)	2060.80	2112.87
Holdout Prediction (MAE)	.155	.197
Optimal Design Specification		
- Shape	Shape 3	Shape 2
- Switch	Trigger	Trigger
- Weight	Light	Light
- Price	$99	$79

Table 16: Objective Product Attributes and Levels for Toothbrush Study

Attribute 1: Price
$1.99
$3.39
$4.59
Attribute 2: Softness of Bristles
Soft
Medium
Attribute 3: Head Size
Compact
Full
Attribute 4: Bristle Design
Design 1: Plain
Design 2: Middle Indicator
Design 3: Three Layers
Design 4: Four Separate Groups
Design 5: Two Circulars
Attribute 5: Angle of Head
Straight Head
Angled Head
Attribute 6: Grip Design
Design 1: Plain Grip
Design 2: Concave without Thumb Grip
Design 3: Concave with Thumb Grip

Table 17: Parameter Estimates on Perceived Effectiveness from the Proposed Model

	Perceived Effectiveness				
Parameter	Subj.#5	Subj.#14	Subj.#36	Subj.#55	Subj.#83
Constant	1.859	4.425	3.550	2.958	1.780
	(.527)	(.647)	(.502)	(.486)	(.556)
Soft	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Medium	.078	.181	-.116	.073	.242
	(.224)	(.236)	(.178)	(.180)	(.134)
Compact	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Full	.277	.365	-.378	.329	.301
	(.207)	(.267)	(.199)	(.186)	(.219)
Plain Bristles	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Middle Indicators	1.707	.780	1.03	.984	1.761
	(.424)	(.535)	(.409)	(.408)	(.416)
Three Layers	3.299	1.085	1.627	1.334	3.427
	(.706)	(.829)	(.652)	(.639)	(.669)
Four Separate Groups	2.777	.906	1.057	2.254	2.836
	(.707)	(.808)	(.659)	(.654)	(.670)
Two Circulars	3.790	.381	1.917	1.835	3.806
	(.724)	(.834)	(.671)	(.653)	(.686)
Straight Head	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Angled Head	.381	.021	.095	.093	.374
	(.209)	(.355)	(.275)	(.239)	(.165)

Posterior standard deviations are in parentheses

Table 18: Parameter Estimates on Perceived Comfort from the Proposed Model

	Perceived Comfort				
Parameter	Subj.#5	Subj.#14	Subj.#36	Subj.#55	Subj.#83
Constant	2.983	4.497	3.806	2.875	3.111
	(.538)	(.653)	(.589)	(.593)	(.510)
Plain Bristles	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Middle Indicators	1.222	.615	.840	1.068	1.035
	(.433)	(.454)	(.392)	(.382)	(.362)
Three Layers	1.96	.740	1.355	1.718	1.747
	(.615)	(.726)	(.590)	(.745)	(.531)
Four Separate Groups	1.795	.844	.734	2.002	1.443
	(.759)	(.655)	(.776)	(.619)	(.678)
Two Circulars	2.100	.026	1.317	1.880	1.772
	(.666)	(.849)	(.637)	(.566)	(.594)
Plain Grip	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Concave w/o Thumb Grip	.394	.142	.216	.340	.292
	(.362)	(.241)	(.339)	(.380)	(.319)
Concave w/ Thumb Grip	.521	.107	.378	.596	.499
	(.355)	(.400)	(.217)	(.366)	(.312)

Posterior standard deviations are in parentheses

Table 19: Parameter Estimates on Purchase Likelihood from the Proposed Model

Parameter	Subj.#5	Subj.#14	Subj.#36	Subj.#55	Subj.#83
Purchase Likelihood					
Constant	-2.758	-2.803	-2.793	-2.767	-2.727
	(.223)	(.225)	(.223)	(.222)	(.222)
Price ($1.99)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($3.39)	-.396	-.446	-.442	-.406	-.397
	(.207)	(.206)	(.199)	(.201)	(.214)
Price ($4.59)	-.783	-.952	-.906	-.788	-.779
	(.242)	(.233)	(.222)	(.250)	(.246)
Soft	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Medium	.135	.189	-.169	.146	.145
	(.185)	(.173)	(.186)	(.102)	(.182)
Compact	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Full	.094	.107	-.161	.179	.095
	(.176)	(.091)	(.182)	(.079)	(.178)
Plain Bristles	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Middle Indicators	.710	.699	.728	.726	.705
	(.251)	(.255)	(.243)	(.251)	(.239)
Three Layers	.927	.991	.891	.928	.882
	(.201)	(.278)	(.213)	(.295)	(.205)
Four Separate Groups	.938	.897	.880	1.057	.915
	(.297)	(.223)	(.284)	(.261)	(.291)
Two Circulars	1.052	.826	1.032	.903	1.071
	(.257)	(.287)	(.253)	(.207)	(.258)
Straight Head	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Angled Head	.121	-.071	.029	.013	.132
	(.109)	(.190)	(.187)	(.194)	(.087)
Plain Grip	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Concave w/o Thumb Grip	.339	.284	.353	.345	.330
	(.259)	(.254)	(.249)	(.256)	(.246)
Concave w/ Thumb Grip	.335	.334	.321	.368	.367
	(.251)	(.240)	(.248)	(252)	(.237)
Perceived Effectiveness	.285	.205	.242	.269	.244
	(.120)	(.121)	(.109)	(.123)	(.119)
Perceived Comfort	.218	.247	.198	.234	.250
	(.116)	(.122)	(.113)	(.118)	(.122)

Posterior standard deviations are in parentheses

Table 20: Parameter Estimates on Purchase Likelihood from Conjoint Model
Using the Same Dataset

	Purchase Likelihood				
Parameter	Subj.#5	Subj.#14	Subj.#36	Subj.#55	Subj.#83
Constant	-1.565	-1.235	-1.326	-1.518	-1.418
	(.307)	(.298)	(.258)	(.286)	(.257)
Price ($1.99)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($3.39)	-.306	-.549	-.526	-.308	-.397
	(.270)	(.253)	(.228)	(.272)	(.246)
Price ($4.59)	-.618	-1.296	-1.202	-.643	-.825
	(.413)	(.398)	(.353)	(.408)	(.376)
Soft	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Medium	.228	.285	-.235	.178	.243
	(.116)	(.251)	(.211)	(.131)	(.112)
Compact	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Full	.097	.221	-.183	.195	.142
	(.209)	(.209)	(.196)	(.114)	(.109)
Plain Bristles	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Middle Indicators	1.306	1.280	1.315	1.311	1.287
	(.283)	(.308)	(.267)	(.280)	(.259)
Three Layers	1.966	1.948	1.786	1.702	1.889
	(.346)	(.385)	(.267)	(.331)	(.284)
Four Separate Groups	1.716	1.757	1.515	2.389	1.636
	(.334)	(.293)	(.324)	(.351)	(.310)
Two Circulars	2.435	1.445	2.078	1.935	2.269
	(.375)	(.372)	(.330)	(.330)	(.323)
Straight Head	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Angled Head	.184	-.071	.108	.103	.227
	(.145)	(.261)	(.136)	(.138)	(.121)
Plain Grip	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Concave w/o Thumb Grip	.547	.334	.415	.553	.497
	(.298)	(.290)	(.264)	(.297)	(.267)
Concave w/ Thumb Grip	.539	.396	.373	.544	.487
	(.268)	(.257)	(.236)	(.268)	(.234)

Posterior standard deviations are in parentheses

Table 21: Parameter Estimates on Purchase Likelihood from Conjoint Model
Using Media Lab Survey

	Purchase Likelihood				
Parameter	Subj.#3	Subj.#13	Subj.#30	Subj.#55	Subj.#60
Constant	-1.507	-1.405	-1.602	-1.567	-1.494
	(.230)	(.232)	(.229)	(.321)	(.227)
Price ($1.99)	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Price ($3.39)	-.363	-.347	-.388	-.363	-.385
	(.241)	(.245)	(.237)	(.255)	(.235)
Price ($4.59)	-.432	-.433	-.472	-.467	-.508
	(.246)	(.206)	(.246)	(.259)	(.243)
Soft	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Medium	.178	.187	.205	.176	.173
	(.190)	(.089)	(.192)	(.198)	(.180)
Compact	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Full	.237	.290	-.192	.221	.235
	(.192)	(.115)	(.199)	(.103)	(.188)
Plain Bristles	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Middle Indicators	.788	.780	1.311	.702	.739
	(.289)	(.298)	(.314)	(.297)	(.282)
Three Layers	1.537	1.496	1.532	1.340	1.551
	(.299)	(.293)	(.309)	(.307)	(.299)
Four Separate Groups	1.315	1.291	.691	1.543	1.273
	(.310)	(.310)	(.285)	(.313)	(.298)
Two Circulars	1.505	1.496	1.506	1.515	1.463
	(.294)	(.302)	(.299)	(.296)	(.291)
Straight Head	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Angled Head	.078	.179	.388	.256	.049
	(.242)	(.102)	(.139)	(.143)	(.235)
Plain Grip	0	0	0	0	0
	(-)	(-)	(-)	(-)	(-)
Concave w/o Thumb Grip	.282	.284	.206	.258	.218
	(.323)	(.226)	(.233)	(.132)	(.327)
Concave w/ Thumb Grip	.728	.245	.328	.252	.721
	(.339)	(.133)	(.239)	(.227	(.332)

Posterior standard deviations are in parentheses

Table 22: Comparison between Proposed Model and Two Conjoint Models

	Proposed Model	Conjoint Model (Same Dataset)	Conjoint Model (Media Lab)
In-Sample Fit (DIC)	4547.730	4604.170	-*
Holdout Prediction (MAE)	.121	.174	.200
Hit Rate	72.6%	65.3%	59.4%
Optimal Design Specification			
- Price	$1.99	$1.99	$1.99
- Softness of Bristles	Medium	Medium	Medium
- Head Size	Full	Full	Full
- Bristle Designs	Two Circulars	Two Circulars	Three Layers
- Angle of Head	Angled	Angled	Angled
- Grip Design	Concave w/ Thumb Grip	Concave w/o Thumb Grip	Concave w/ Thumb Grip

*DIC value for conjoint model conducted in Media Lab is not reported here because the assumption of DIC comparison is based on the same dataset.

Table 23: Latent Class Conjoint Part-worth Estimates

	Segment 1	Segment 2	Segment 3	Segment 4
Segment Size	0.378	0.248	0.121	0.253
	Part-worth	**Part-worth**	**Part-worth**	**Part-worth**
Own Brand	-0.545	0.454	2.211	-0.165
Brand 1	0.183	1.063	-2.372	-0.203
Brand 2	0.832	0.112	-1.589	1.153
Brand 3	-0.470	-1.629	1.741	-0.785
Price $79	-0.111	-0.091	0.005	-0.015
Price $99	-0.892	-1.154	1.919	-0.244
Price $129	1.003	1.245	-1.923	0.259
Amp 6	1.254	0.453	-1.481	-0.457
Amp 9	0.132	-1.422	-0.653	-2.381
Amp 12	-1.386	0.969	2.134	2.838
Life 80	-0.863	-0.127	-4.717	0.802
Life 110	1.337	-0.471	-5.825	0.743
Life 150	-0.474	0.598	10.542	-1.545
Paddle	0.428	0.299	-3.291	-0.651
Top Slider	-1.015	-0.653	-3.045	0.415
Side Slider	2.392	-0.073	2.463	0.563
Trigger	-1.805	0.427	3.873	-0.327
Actuator A	1.510	0.718	1.512	0.415
Actuator B	-1.510	-0.718	-1.512	-0.415
None	-0.022	-0.022	-0.022	-0.022

Table 24: Design Parameters' Information

Design Parameter	Nominal	Lower bound	Upper bound
Source Voltage (V)	110	95	125
Ambient Temperature (C)	25	-10	50
User Load Bias (lb)	6	3	9
Fan CFM Degradation (%)	0	0	80
Application Torque Adjustment (%)	0	-20	20

Table 25: MOGA parameters

Parameter	Value
Population Size	100
Population Replacement	10
Crossover Probability	90%
Mutation Probability	5%
Selection Type	Stochastic Universal Selection
Number of Iterations	100

FIGURES

Figure 1: Overall Framework
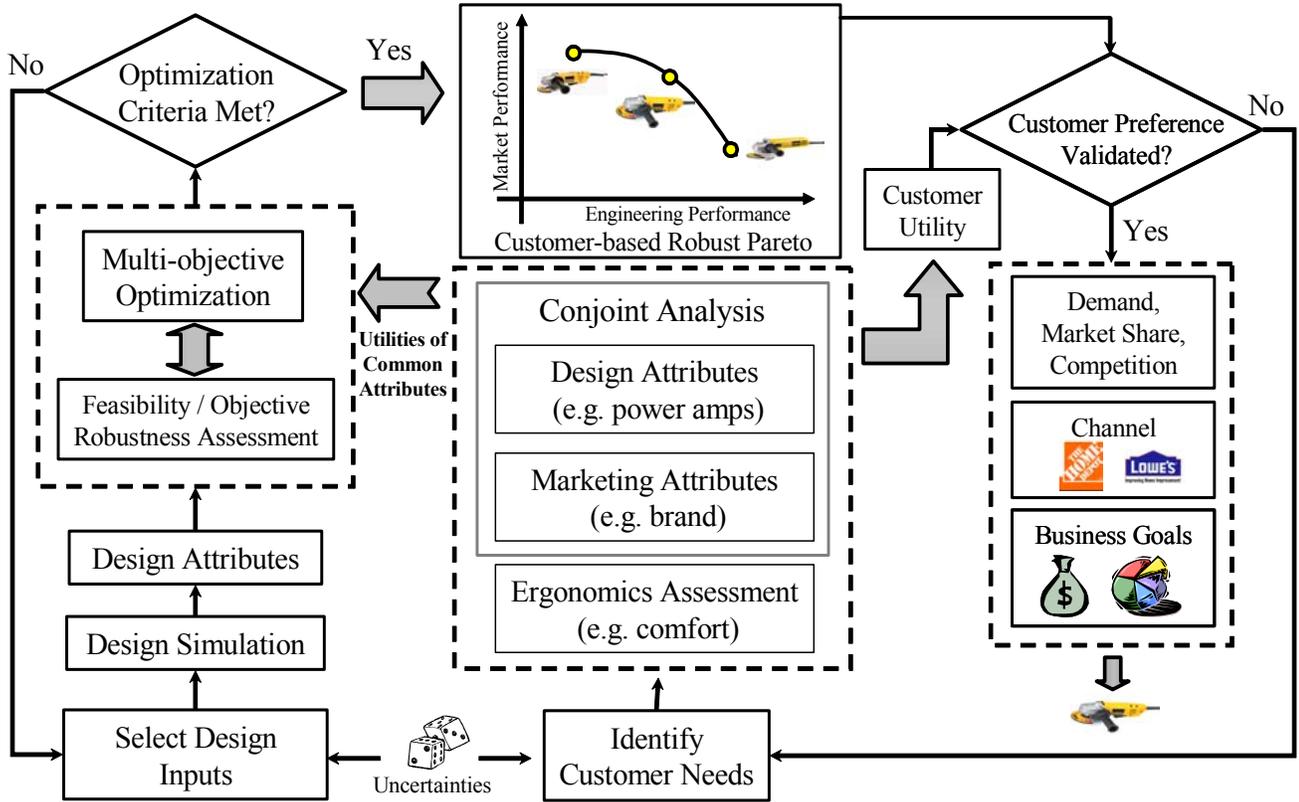
Figure 2: Estimation of Market Specifics – Before Entry

Individual Consumer Preferences

Choice Based Conjoint

Hierarchical Bayesian Estimation

Conjoint Estimates
Market Share Estimates

Market Level Data

Observed Retail Prices

Retailer's Profit Maximization
Market Equilibrium Conditions

Calculate Wholesale Prices
(Retail Margins)

Conjoint Estimates
Wholesale Prices

Incumbents' Profit Maximization
Market Equilibrium Conditions

Calculate Marginal Costs of Production
(Manufacturer Margins)

Figure 3: Market Scenario Development – After Entry of Design Alternative
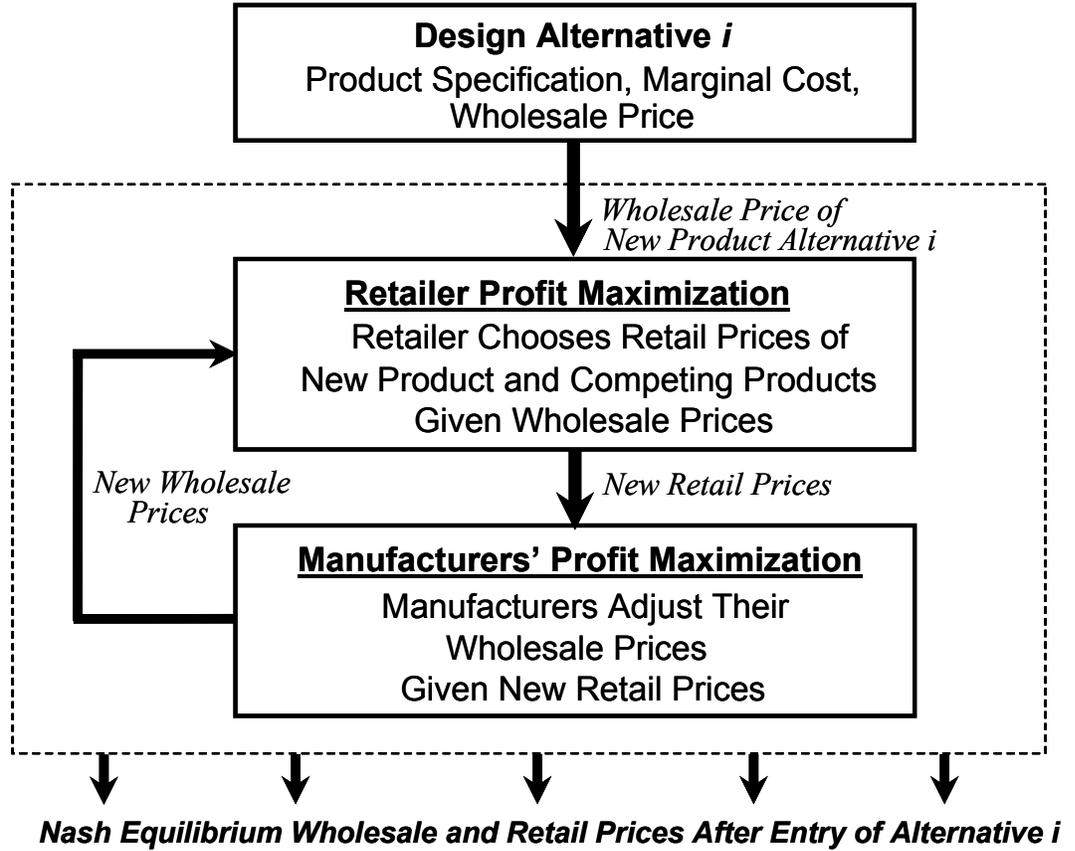
Figure 4: Proposed Model: An Example of a Power Tool Evaluation

Note: Solid lines and arrows represent the relations considered in a traditional c onjoint model. Dotted lines and arrows represent the unique relations incorporated in our proposed model.
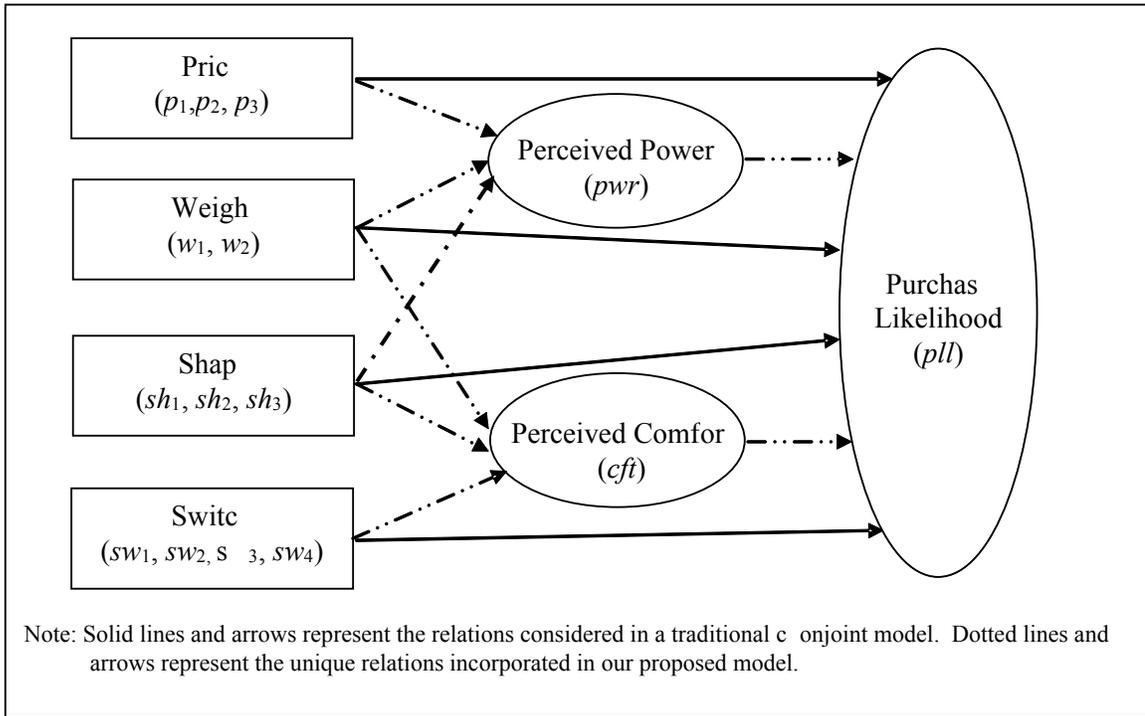
Figure 5: Proposed Model: An Example of a Toothbrush Evaluation

Note: Solid lines and arrows represent the relations considered in a traditional conjoint model. Dotted lines and arrows represent the unique relations incorporated in our proposed model.
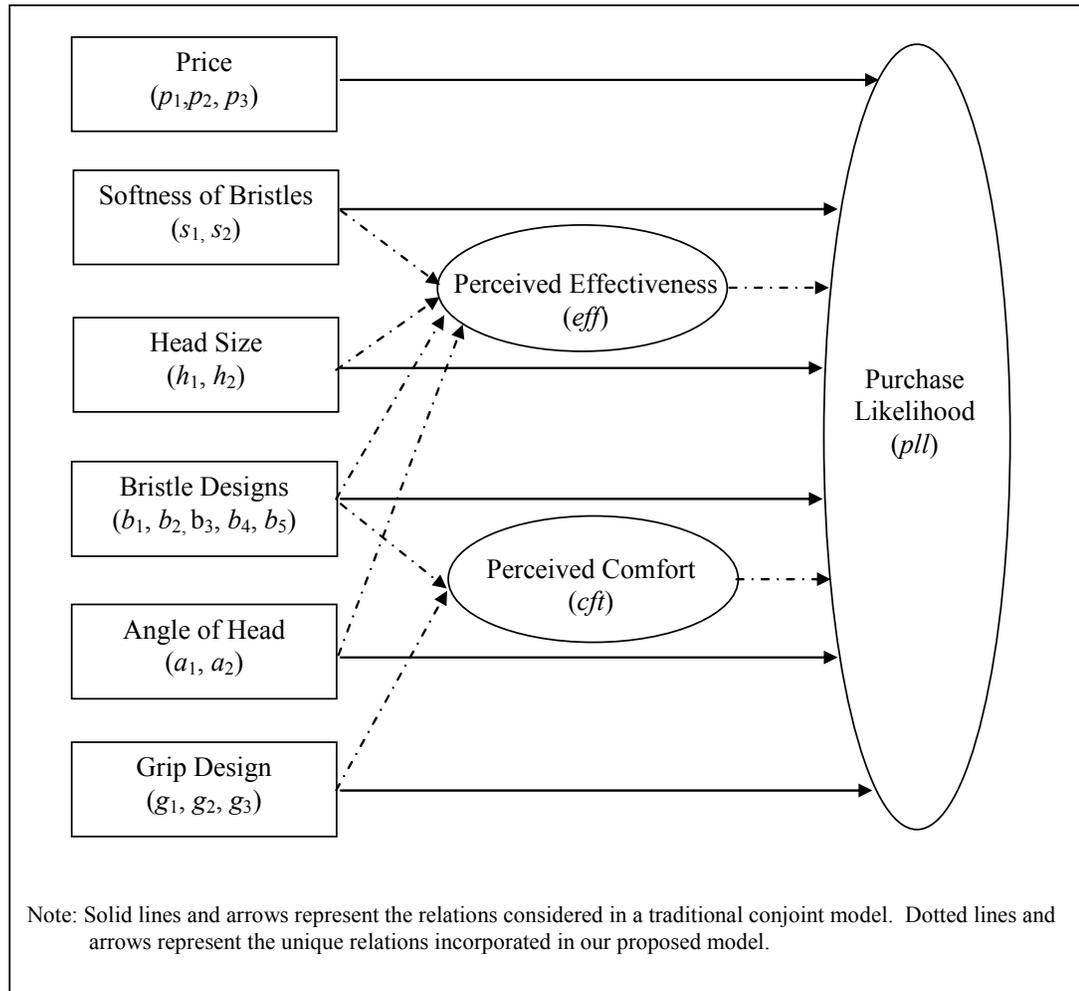
Figure 6: The Overall Framework
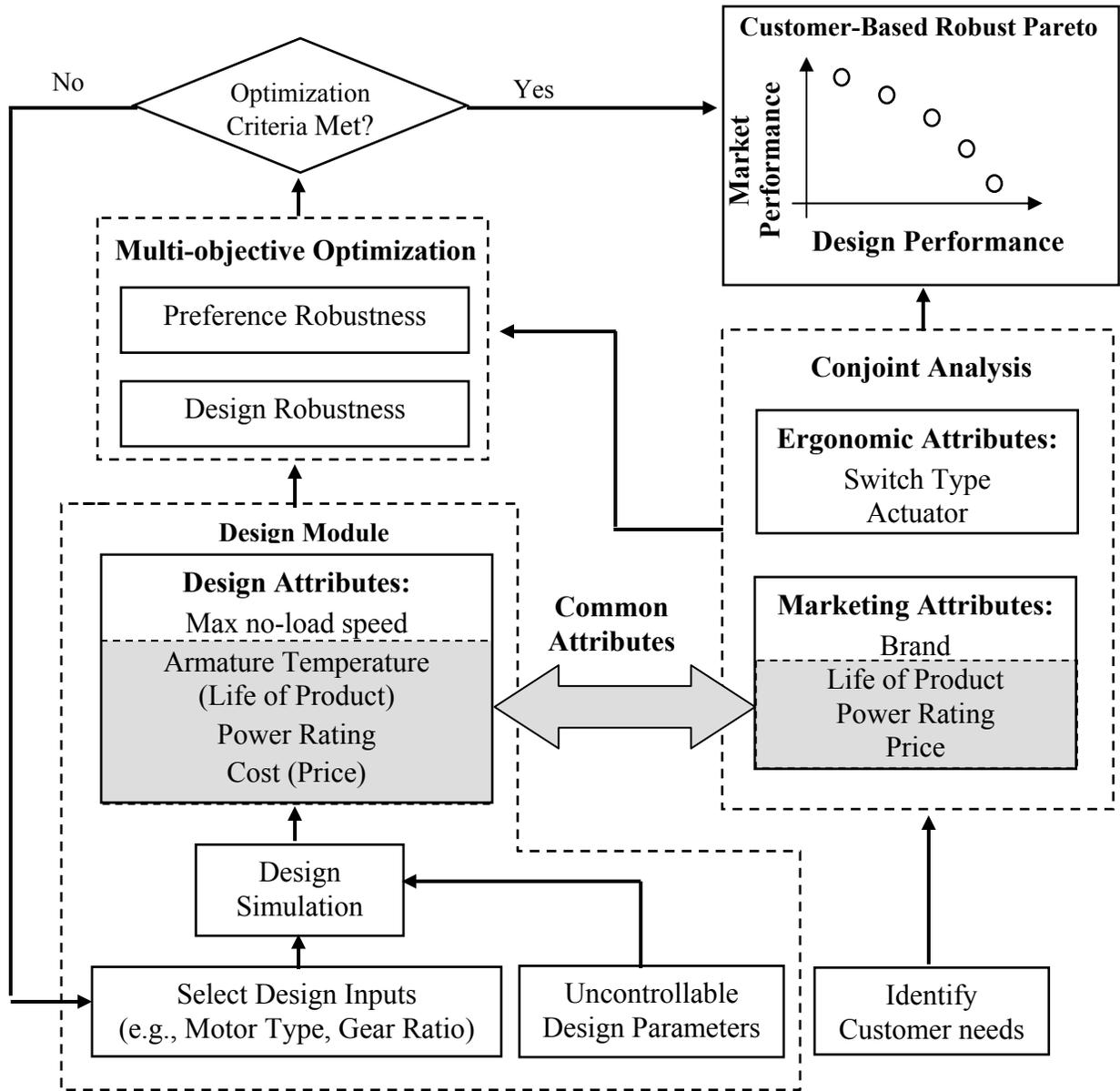
Figure 7: Mapping from Design Parameter Space to the Attribute Space
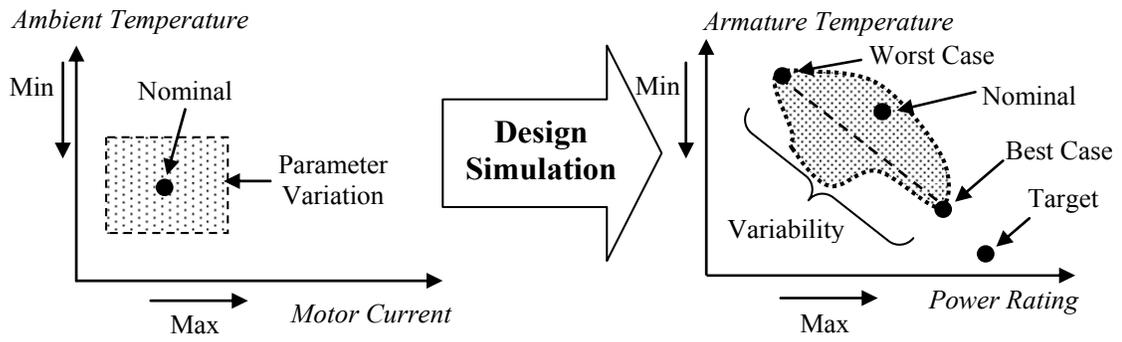
Figure 8: Multi-Objective Robustness Comparison of Two Design Candidates
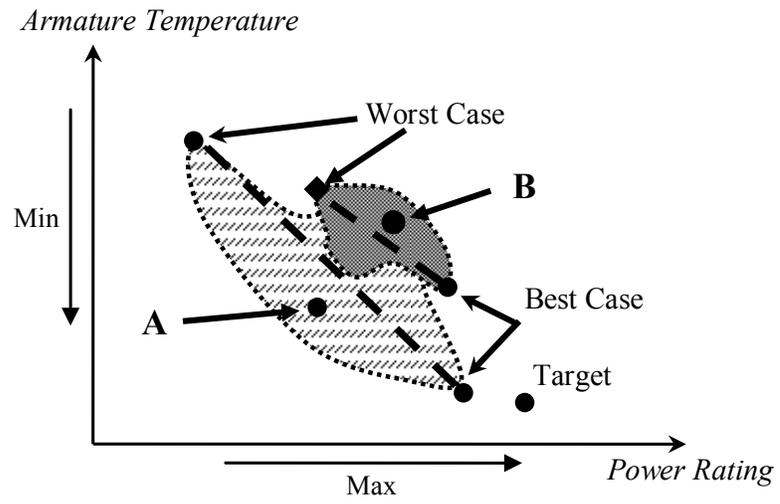
Figure 9: Preference Robustness of the Product
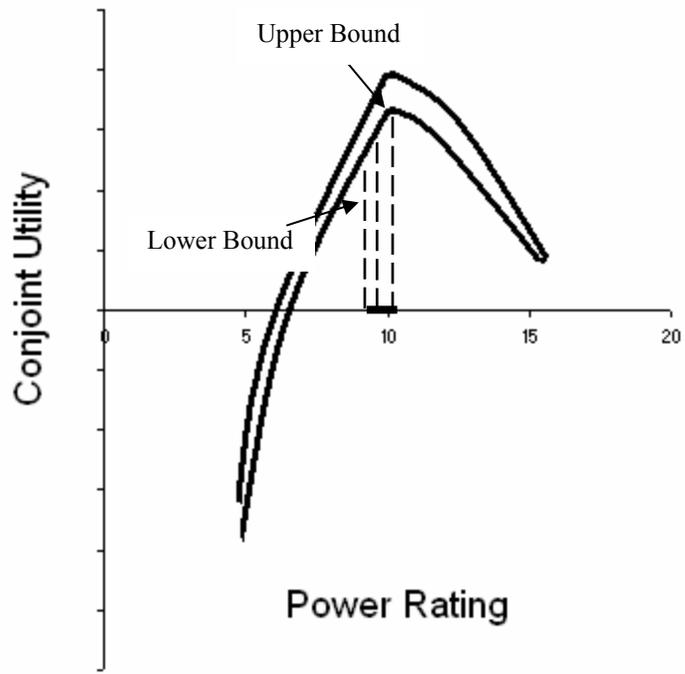
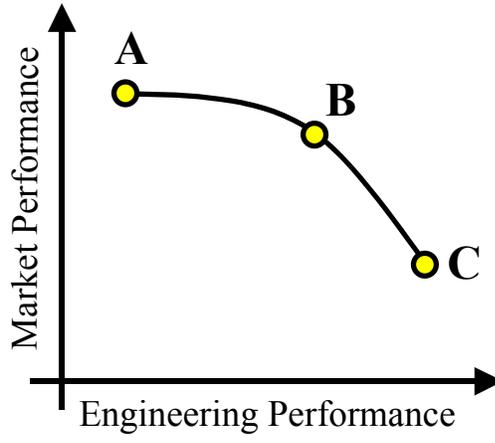Figure 10: Integrated Robust Optimization Approach
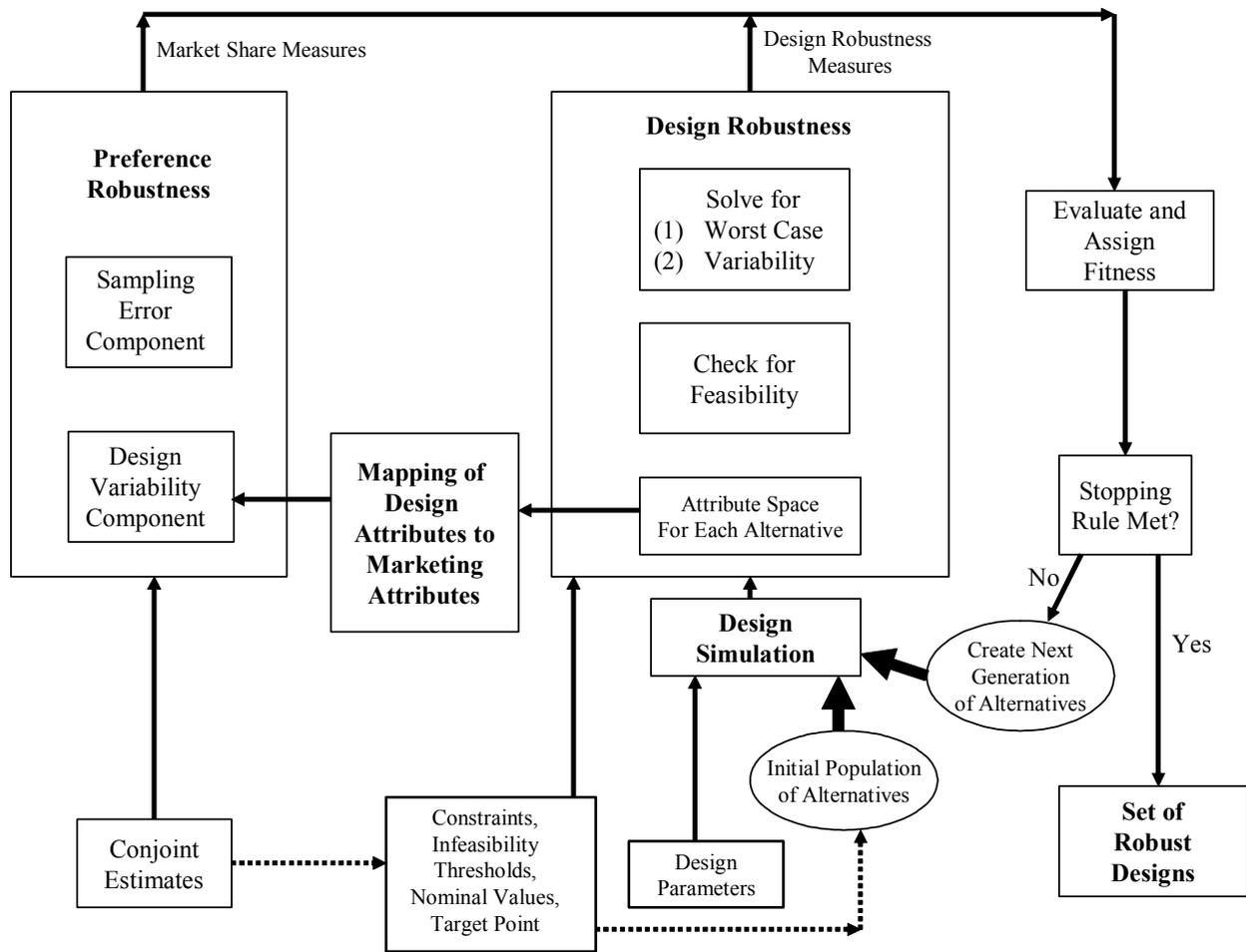
Figure 11: Customer-Based Pareto Designs

APPENDICES

APPENDIX 1: EXISTENCE OF POSITION-PRICING EQUILIBRIUM IN MIXED

STRATEGIES

In this appendix, we illustrate an example of where competitive reactions extend beyond price. We simplify the competitive reaction for ease of demonstration. The essence of our approach applies to a more general context by enumeration of possible scenarios involved with the feature changes and developing price equilibriums under each scenario.

Assuming that in the consideration of introducing alternative number 10 with a new type of switch (top slider switch), the focal manufacturer speculates that the manufacturer of incumbent product X is likely to change its switch type to a top slider switch as a competitive move. Currently having a side slider switch, the manufacturer of incumbent product X can move a slider switch from the side to the top of the product without significantly changing the entire design of product. As a result, the focal manufacturer may want to consider the possible move from this manufacturer before it decides whether to put a top slider or side slider switch on its new product. The interaction between the focal manufacturer and this competitor can be characterized as follows. First, each manufacturer predicts the end result of the price equilibrium for any positioning decision. Second, the manufacturers make the positioning decision accordingly. This decision process is quite reasonable because changes in switch type are more "sticky" and more difficult to make than price decisions.

Adopting our framework, we estimated the equilibrium profits ($ in millions) for

the focal manufacturer and the manufacturer of product X under all 4 possible positioning

decisions, assuming there is no cost associated with the relocation of the slider switch.

The results are given in Table 9. According to Table 9, the only equilibrium results from

this simultaneous move game is that: the manufacturer of the new product chooses a top

slider switch and the manufacturer of incumbent product X keeps its side slider switch.

<Insert Table 9 about here>

For a different scenario, we may not have such a pure strategy equilibrium.

However, a mixed strategy equilibrium always exists for a finite game (Nash 1951). In

our framework, the strategy set for each manufacturer j (j = 1,…,J+1) is the attribute

space defined by the conjoint analysis. Therefore, the strategy set A_j is finite for each

manufacturer j (j = 1,…,J+1). The payoff function in this game is the manufacturer's

profit function. In a simultaneous move game, each manufacturer will first predict the

end result of the price equilibrium for any positioning decision. After accounting for

channel acceptance, if a pure strategy equilibrium does not exist, a mixed strategy Nash

equilibrium can always be solved in which the manufacturers choose probability

distributions over the non-price product attributes. It should also be noted that such

mixed strategy equilibrium may not be unique (Nash 1951).

APPENDIX 2: HIERARCHICAL BAYES PROCEDURES

The estimation of part worths follows an iterative procedure (Allenby and Ginter 1995). We start with the initial estimates (priors) of the $v_i = (\beta_i{}', a_i)'$ parameters for each individual. These initial v_is are approximate least square estimates, where the dependent variable consists of choices coded as 0 and 1. Our priors for the vector v are the average of the initial v_is. And the prior of the variance-covariance matrix D consists of the variances and covariances of the initial v_is.

Given the priors of the parameters to be estimated, each iteration consists of the following steps. *First,* using the present estimates of the v_is and D, a new estimate of the population v is generated as the mean of current v_is and with covariance matrix D/n. A new v is then drawn from that distribution. *Second,* using the present estimates of v_is and $v,$ a new estimate of D is generated from the inverse Wishart Distribution. *Third,* using the current estimates of v and D, new estimates of v_is are generated using the Metropolis Hastings Algorithm as follows: We first generate a new estimate for v_i and test whether the posterior probability of the new v_i increases as compared to the estimate from last draw. The posterior probability is calculated as the product of prior probability from previous estimate and the likelihood function. If the new estimate of v_i represents an improvement, we accept it as our next estimate. If not, we accept or reject the new estimate depending on how much worse it is as compared to the previous estimate. This iteration process continues until the parameter estimates converge. After the convergence occurs, we let the iteration process continue for many further iterations and the final

estimates for v_is, v, and D are obtained by averaging the posterior draws after the

convergence.

APPENDIX 3: PRICE EQUILIBRIUM AMONG OLIGOPOLISTIC

MANUFACTURERS

This proof of the price equilibrium among oligopolistic manufacturers follows the

proof outlined by Anderson, De Palma, and Thisse (1992). The profit function for

manufacturer j $(j = 1,\ldots,J+1)$ is as follows. These functions are payoff functions of the

manufacturers.

$$\max_{w_j} \pi_j^m = (w_j - c_j) * m_j * S - F_j \quad j = 1,\ldots,J+1 \quad (C1)$$

Theorem (Anderson, De Palma, and Thisse 1992): If the strategy sets S_j, for all j

$= 1,\ldots,J+1$, are compact and convex and if the profit function π_j^m, for all $j = 1,\ldots,J+1$,

are continuous in $(w_1, w_2, \ldots, w_{J+1})$ and quasi-concave in w_j, then there exists a price

equilibrium.

In our model, the wholesales selected by the manufacturers have to be in between

the retail prices and the marginal costs of the products. Therefore, the strategy sets S_j, for

all $j = 1,\ldots,J+1$, are compact and convex. It is obvious that the profit function π_j^m, for all j

$= 1,\ldots,J+1$, are continuous in $(w_1, w_2, \ldots, w_{J+1})$. It remains to be shown that π_j^m is quasi-

concave in w_j, for $j = 1,\ldots,J+1$. To simplify notation, set X_j as the market share of

manufacturer j when the wholesale price of own product is w_j and the wholesale price of

other products are w_{-j}. Namely, $X_j \equiv m_j(w_j, w_{-j})$.

As noted by Caplin and Nalebuff (1991), a sufficient condition for π_j^m to be

quasi-concave in w_j is that $1/X_j$ be convex in w_j. To see this, assume that $1/X_j$ is

convex but that π_j^m were not quasi-concave in w_j. Then, there exist $w_j^{'}$ and $w_j^{''}$ in the strategy set S_j such that $w_j^{'} < w_j^{''}$ and

$$\pi_j^m(w_j^{'}, w_{-j}) > \pi_j^m(w_{j\theta}, w_{-j}) \qquad (C2)$$

and $\quad \pi_j^m(w_j^{''}, w_{-j}) > \pi_j^m(w_{j\theta}, w_{-j}) \qquad (C3)$

Where $w_{j\theta} = \theta w_j^{'} + (1-\theta) w_j^{''}$ and $0 < \theta < 1$. Denote $X_j^{'} \equiv m(w_j^{'}, w_{-j})$,

$X_j^{''} \equiv m(w_j^{''}, w_{-j})$, and $X_{j\theta} \equiv m(w_{j\theta}, w_{-j})$. Divide inequality (C2) by $X_j^{'} X_{j\theta}$ and inequality (C3) by $X_j^{''} X_{j\theta}$ to obtain:

$$\frac{w_j^{'} - c_j}{X_{i\theta}} > \frac{w_{j\theta} - c_j}{X_j^{'}} \qquad (C4)$$

and $\quad \dfrac{w_j^{''} - c_j}{X_{i\theta}} > \dfrac{w_{j\theta} - c_j}{X_j^{''}} \qquad (C5)$

Multiplying inequality (C4) by θ and inequality (C5) by $(1-\theta)$, and summing the resulting expressions yields:

$$\frac{w_{j\theta} - c_j}{X_{j\theta}} > \frac{\theta(w_{j\theta} - c_j)}{X_j^{'}} + \frac{(1-\theta)(w_{j\theta} - c_j)}{X_j^{''}} \qquad (C6)$$

Since $w_{j\theta} - c_j > 0$, this inequality violates the convexity of $1/X_j$ and we arrive at a contradiction. Therefore, the convexity of $1/X_j$ implies that the quasi-concavity of π_j^m over the strategy set S_j. This in turn means that π_j^m is quasi-concave on S_j and a price equilibrium exists by the Theorem given above.

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