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New Product Development Under Channel Acceptance

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In channel structures characterized by a powerful retailer (e.g., Wal-Mart, Home Depot), the dominant retailer's acceptance of a manufacturer's new product often determines the success of the new offering. Focusing on a manufacturer in such a market, we develop an approach to positioning and pricing a new product that directly incorporates the retailer's acceptance criteria into the development process. Our method also accounts for the retailer's product assortment and the competing manufacturers' potential reactions in wholesale prices. Our method merges individual-level conjoint models of preference with game-theoretic models of retailer and manufacturer behavior that are specific to the institutional setting of the focal manufacturer. The application of our approach in the context of a new power tool development project undertaken by this manufacturer also highlights the potential of our approach to other analogous institutional settings.

Key words: new product forecasting; product positioning; distribution channel; conjoint model; game theory; big-box retailers; retailer acceptance; Wal-Mart; Home Depot
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1. Introduction

The new product development process has generally focused on the consumer and ways to incorporate their preferences in developing new products, using methodologies such as conjoint analysis. However, focusing on the consumer alone can be insufficient, given that big-box retailers such as Wal-Mart, Home Depot, and Toys R Us have become dominant in many product markets (Schiller et al. 1992, McCormack 1997). Consumers prefer these big-box retailers because of their low prices, attractive assortments, and close proximity (Cappo 2003). For many product categories, they have become the first place most consumers shop when considering a purchase. With the power concentrated among these retailers, the refusal of such a retailer to carry a new product can effectively block its national distribution (Felgner 1989).

With this emerging clout, these dominant retailers have become gatekeepers for the numerous new products and line extensions introduced by the manufacturers. While consumers may prefer more variety, limited shelf space motivates dominant retailers such as Home Depot and Wal-Mart to employ category management in their new product acceptance decisions (Bounds 2005). Recognizing retailers' control of market access, manufacturers have been looking for a practical solution to address the problem of channel acceptance early on in the new product development process (Lucas 1996). Academic marketing 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, p. 268) and McLaughlin and Rao (1991) highlight that channel acceptance of new products is a topic that deserves investigation. Urban and Hauser (1993) emphasize that the manufacturers should be prepared to include the retailer's preferences in their decisions to introduce new products, given the increasing power of retailers.

In this paper, we respond to this need for a practical model that incorporates the retailer's acceptance decision into the manufacturer's new product choice. We present a method to incorporate the retailer's acceptance in the new product introduction of a large consumer durable goods manufacturer, and we provide a prototypical application to one product category. Within the institutional context in which the manufacturer operates, we merge consumer preference data obtained in a conjoint experiment with game-theoretic models to estimate how the retailer and the competing manufacturers will react to the specific new product concepts, and whether the retailer would find a given concept acceptable. While existing models of predicting new product success tend to predict only consumer acceptance without considering channel behavior, we explicitly model 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. We also model the expected reactions of the incumbent manufacturers to the launch of a new product. To make the approach applicable to solving an actual problem, the model we develop must be geared to the institutional setting in which the manufacturer operates. Because the general methodology should have significant appeal for analogous contexts, we also discuss ways in which our framework can be modified to apply to different contexts.

We have organized the paper as follows. In §2, we discuss the institutional setting that defines the scope of the study and framework. We also discuss analogous settings where our framework will be useful. In §3, we present the theoretical rationale for our framework in the context of the institutional setting. We also present the methodological details of our approach. Section 4 describes the empirical application. In §5, we discuss several model extensions that go beyond the scope of our institutional setting. We conclude in §6 with a discussion on the contributions and limitations of our approach, and avenues for future research.

2. The Institutional Setting

The focal manufacturer in our study is a large multinational consumer durable goods manufacturer competing with several other large multinational firms with similar but differentiated products in the U.S. market characterized by a dominant retailer. The focal product category, a handheld power tool, is targeted towards metal and construction workers who buy their own tools, with the dominant retailer controlling much of the access to the market. Manufacturers have a strong incentive for acceptance of their products in this channel due to the large volumes handled by the dominant retailer. The second-largest retailer in this product category is considerably smaller, carrying only two store brands. While there may exist some strategic influences from this competing retailer, it is reasonable to assume that they are negligible. We provide a sensitivity test of this assumption later in §5.

Our discussions with our industrial partner indicated that manufacturers in this category post a wholesale price for their products to the retailer. If the retailer decides to carry the product, the retailer sets the retail price. The acceptance or rejection of these new products is done during line reviews held by the retailer. These involve the review of a large number of products offered by the manufacturer to the retailer. The time devoted to any specific product is minimal, and ordinarily there is no negotiation between the manufacturer and retailer on wholesale prices.[1] Hence, we make the corresponding assumption in our strategic model. The line reviews allow the dominant retailer to benefit from the intense competition in new product entries. Therefore, the retailer avoids making any commitment on new product acceptance or dictating the desired product positioning and pricing to the manufacturers.

An important characteristic of the manufacturer-retailer setting is the uniform pricing structure. Various channel coordination mechanisms (such as two-part pricing, slotting allowances, and quantity discounts) are absent in our setting.[2] One possible reason for this is that the competition between manufacturers in the product market keeps them from reaching the collusive agreements needed to enforce the coordination mechanisms (Shaffer 1991). Another reason is that the focal product belongs to a mature category in which both the manufacturers and the retailer have good knowledge about the end users' preferences and demand, thus obviating the need to use slotting allowances or two-part pricing to communicate private information regarding product demand.[3] This pricing practice is likely in many other mature categories, so this institutional setting can have many analogies in which our approach can be useful.

Given that the product market is mature, the new products introduced in the focal category tend to be "continuous innovations" rather than "paradigm

[1] Given that the manufacturers and the retailer have an ongoing relationship across multiple product categories, this is probably the most effective way of contracting in order to minimize transaction costs, especially for smaller categories such as the handheld power tools that we focus on (see Desai et al. 2004).

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

[3] Lariviere and Padmanabhan (1997), Desai (2000), and Sudhir and Rao (2006) show conditions under which slotting allowances are common. One important finding (normative as well as empirical) is that they are useful when the uncertainty about product success is the greatest, a condition that is not common in mature markets with incremental product improvements and continuous innovations.

shifts." Consumers have good knowledge of the product category, and thus their inputs regarding product features and preferences can be quite useful for new product development. New products are introduced by a manufacturer every four to five years, and nonprice attributes of the incumbent products are typically not altered in the short term.

In summary, the product market is characterized by competing manufacturers and a decentralized dominant channel partner, with uniform pricing structure. Manufacturers determine product design and set wholesale prices, while the retailer is interested in maximizing category profit in making the product acceptance decisions, using a line review process. It is within this context that we propose our framework to help the focal manufacturer to identify the optimal product design that satisfies the needs of both the end users and the dominant retailer, while maximizing the manufacturer's profitability.

3. Application Framework

3.1. Development of Application Framework for the Institutional Setting

Our analysis 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. Given the focus of our approach on accurate market forecasting, we use a choice-based hierarchical Bayesian conjoint model to obtain individual-level consumer preferences.[4] We collect data from the group of consumers who consider the dominant retailer as their primary store choice. We include "outside goods" in the consumer choice model, which implicitly allows for purchases at some competing retailers. As stated earlier, the relatively small presence of the main competing retailer in this category makes it unlikely that this retailer plays a major strategic role for this product.[5] In the first stage of our analysis, we also employ a model of manufacturer-retailer interaction to determine retail and wholesale costs, margins, and profits given our demand estimates. This model is based on an assumption that manufacturers maximize profits for their own product, and that the dominant retailer maximizes category profits.[6]

In the second stage, using the estimates obtained in Stage 1, 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*. As indicated earlier, the adjustment of the nonprice attributes occurs only every four or five years as part of a new product introduction in the market we study. Consequently, we model competitive reactions to new product introductions by changes in wholesale price only, which is consistent with the extant literature in product positioning and pricing (Carpenter 1989, Hauser 1988, Horsky and Nelson 1992, Moorthy 1988).[7]

We denote the market forecast of each possible product position as one market scenario. In each scenario, we solve for the Nash equilibrium retail and wholesale prices after the introduction of each design alternative. This follows from our assumption of no negotiations during new product introductions, which were discussed earlier. Because both the manufacturers and the retailer have good knowledge about the end users' preferences and the specifications of product exchange in the distribution channel, the existence of Nash equilibrium profits for both the manufacturers and the retailer is sufficient to remove any incentive for negotiation (Iyer and Villas-Boas 2003).

The search for the Nash equilibrium prices involves substituting the individual-level conjoint partworths into the retailer and the manufacturers' profit maximization functions. We solve a numerical optimization problem for both the retailer and the manufacturers simultaneously. In the application framework, we use an iterative estimation procedure to solve this game. This procedure extends the methods introduced by Horsky and Nelson (1992) and Green and Krieger (2004) by incorporating both the retailer's profit maximization problem and the

[4] The hierarchical Bayes procedure is one of several alternatives that could be employed. Some other methods that estimate consumer preferences from choice scenarios could also be used (e.g., Cui and Curry 2005, Evgeniou et al. 2005, Hauser and Toubia 2005). Our use of conjoint contrasts to the use of aggregate-level parameters to specify consumer demand, as commonly used in New Emperical Industrial Organization (NEIO) literature; see Sudhir 2001a, Villas-Boas and Zhao 2005.

[5] Other reasons for this conclusion are that the market for the focal category is a small component of any store's revenue; consumers' store-choice decisions are more likely to be dictated by factors that are independent of the category, such as their proximity to the stores; it is unlikely that consumers would shop across stores to compare items in this low-to-medium ticket category (Chintagunta et al. 2003).

[6] While the retailer wishes to optimize over its entire set of products, this would require data on cross elasticities that would be virtually impossible to obtain, given the large number of SKUs that it carries. Users of our method should bear in mind that maximizing over additional categories (complementary products, for example) may yield slightly lower optimal prices.

[7] Also, it is possible that only a mixed-strategy equilibrium exists if other attributes are modified (Choi and DeSarbo 1993). The use of such strategies is limited in practice because "a firm would not throw a dice on a new product feature as implied by the mixed strategy" (Choi and DeSarbo 1993, p. 341).

individual-level consumer preference estimates into our framework.

After we obtain the equilibrium retail and wholesale prices for each market scenario, the design alternative will be retained for further consideration only if it can increase the category profit for the retailer. Among the remaining design alternatives, the optimal product is chosen as the one that maximizes the focal manufacturer's profit.

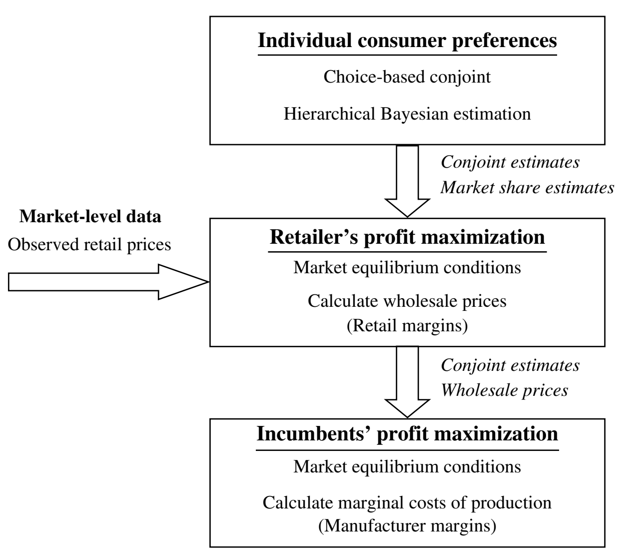
To summarize, in the context of our institutional setting we have developed a formal procedure readily available for the manufacturers to incorporate channel acceptance into the new product development process. Our framework extends the existing literature by explicitly modeling the category management decisions by the retailer so that the retailer's preference is accounted for in the new product introduction decisions, as well as the needs of the end users and the potential reactions from the competing manufacturers. Next, we provide the specifics of our approach.

3.2. Specifics of Our Approach

3.2.1. Before New Product Entry. Before new product entry, the estimation of the market specifics by the new product manufacturer is schematically shown in Figure 1.

Estimating Individual Consumer Preferences. We assume that each consumer has an ideal product specification defined by the product features. Given a particular product specification, the consumer always prefers a lower-priced product (e.g., between two power tools with identical product features, a lower-priced tool is preferred). Prior to the new product entry, the focal manufacturer collects individual consumer-level data using a choice-based conjoint experiment and estimates consumer references using the hierarchical Bayesian estimation technique.

Figure 1 Estimation of Market Specifics—Before Entry



The consumer demand function is defined 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:

$$U_i(\mathbf{x}_{gk}, p_{gk}) = (\mathbf{x}'_{gk}\beta_{ix} + p_{gk}\beta_{ip}) + \varepsilon_{igk}, \tag{1}$$

where $\mathbf{x}_{gk}$ = a $s \times 1$ 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 $s \times 1$ 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.

The retail price is coded as a continuous variable, while the other product attributes are coded as effects-type discrete variables. At the individual level, the probability of individual i choosing profile g from choice set k is expressed using the familiar logit expression.

$$\Pr_{igk} = \frac{\exp(\mathbf{x}'_{gk}\beta_{ix} + p_{gk}\beta_{ip})}{\sum_{g'=1}^{G}[\exp(\mathbf{x}'_{g'k}\beta_{ix} + p_{g'k}\beta_{ip})] + \exp(a_i)}, \tag{2}$$

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

As stated earlier, the no-choice option in Equation (2) serves as a base alternative to account for retail competition in the form of outside goods and possible market expansion with the introduction of the new product (Haaijer et al. 2001). Assuming that the individual part-worths have a multivariate normal distribution, the estimation is accomplished by using the hierarchical Bayes procedure (Allenby et al. 1998, Orme 1998). This set of part-worth estimates is used to characterize individual consumer preferences in our application framework.[8]

Before the introduction of the new product, there are J incumbent competitive products carried by the dominant retailer. Assuming, as is realistic for this

[8] When representing choice alternatives as bundles of product features, researchers often have to omit some attributes in their choice experiments. Accordingly, consumers may use price to make inference about the omitted attributes (Rao and Sattler 2000). Our price estimates are subject to this potential problem. Several characteristics of our study may help to lessen this bias (Rao and Sattler 2000; Rao and Monroe 1989, 1996). First, the respondents were told that all the features absent in the study should be considered to be identical across products. Second, the attributes in the study were carefully selected as the most crucial for the consumers. Finally, this is a repeat-purchase product category with generally knowledgeable consumers.

durable category, that each individual will only purchase one unit of the product at the time of purchase, the market share of each incumbent product can be estimated using the conjoint part-worth estimates.[9]

Estimating Wholesale Prices and Marginal Costs of Incumbent Products. We estimate the wholesale prices and the marginal costs of the incumbent products prior to the entry of the new product in an NEIO framework. As explained earlier, we assume that the dominant retailer sets the retail prices to maximize its category profit. Before the introduction of the new product, the retailer's profit maximization can be written as:

$$\max_{p_1, p_2, \ldots, p_J} \pi^r = \left\{\sum_{j=1}^{J}[m_j * (p_j - w_j) * S]\right\} - sc * J, \qquad (3)$$

where
π^r = the category profit of the retailer
m_j = the market share of product j
w_j = the wholesale price of product j
S = market size (in units of potential purchase)
sc = marginal shelf cost (assumed constant)[10]

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

$$\max_{w_j} \pi_j^m = (w_j - c_j) * m_j * S - F_j \quad j = 1, \ldots, J, \qquad (4)$$

where
c_j = the marginal cost of product j
F_j = the fixed cost of product j

We assume that the retailer's pricing decisions are a function of wholesale prices, which are determined by the manufacturers. There are three reasons behind this assumption of manufacturer Stackelberg price leadership. First, this assumption conforms to the actual procedure in the product category. In practice, the retailer will not make a commitment to carry a product without knowing the wholesale price commanded by the manufacturer. Second, this assumption has substantial theoretical and empirical support in the channel and the NEIO literature, particularly for an oligopoly product market with a few manufacturers (e.g., Betancourt and Gautschi 1998, Coughlan and Wernerfelt 1989, Shaffer and Zettelmeyer 2002, Sudhir 2001a, Villas-Boas and Zhao 2005). Third, the estimates from the alternative models of vertical Nash and retailer Stackelberg lacked face validity (unusually low wholesale margins under both models and unusually high retail margins under retailer Stackelberg).[11]

Based on the conjoint part-worths, the market share estimates of the incumbent products, the observed retail prices, and the first-order conditions (FOCs) of Equation (3), we can estimate the wholesale prices $(w_1, w_2, \ldots, w_J)$ of the incumbent products (Appendix A). Accordingly, the retail category profit before new product entry can be calculated.

Next, deriving the FOCs from Equation (4) and making the appropriate substitutions from the retailer's FOCs, we can calculate the marginal cost of production for each incumbent product as follows ("^" is used here to represent the estimated parameters) (Appendix A):

$$c_j = \widehat{w}_j + \frac{\widehat{m}_j}{\left(\frac{\partial \widehat{m}_j}{\partial p_1}, \frac{\partial \widehat{m}_j}{\partial p_2}, \ldots, \frac{\partial \widehat{m}_j}{\partial p_J}\right) \widehat{G}^{-1} \left(\frac{\partial \widehat{m}_j}{\partial p_1}, \frac{\partial \widehat{m}_j}{\partial p_2}, \ldots, \frac{\partial \widehat{m}_j}{\partial p_J}\right)'} \quad j = 1, \ldots, J, \qquad (5)$$

where $\widehat{G}_{J\times J}$ is a $J \times J$ matrix with the jkth element as:

$$\hat{g}_{jk} = \frac{\partial \widehat{m}_j}{\partial \hat{p}_k} + \frac{\partial \widehat{m}_k}{\partial \hat{p}_j} + \sum_{j'=1}^{J}\left[(p_{j'} - \widehat{w}_{j'}) \frac{\partial^2 \widehat{m}_{j'}}{\partial \hat{p}_j \partial \hat{p}_k}\right]. \qquad (6)$$

The above method of estimating wholesale prices and marginal costs has provided estimates with good face validity that generally agreed with the assessments of our industrial partner. 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.

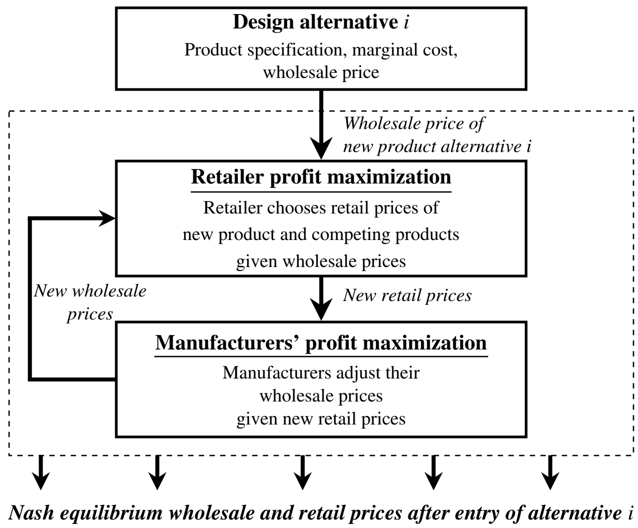
3.2.2. After New Product Entry. The manufacturer has a finite set of design alternatives defined by enumerating all the possible combinations of attribute levels in the conjoint study. Based on the product specification, we assume that the focal manufacturer can approximate the marginal cost for each alternative. The manufacturer's goal is to select a product specification and a wholesale price that: (1) will be accepted by the dominant retailer, and (2) is most profitable as compared to the other design alternatives that are acceptable to the retailer. In meeting this objective, the manufacturer takes the following factors into consideration: (1) the locations of the incumbent products, (2) individual consumers' responses to new

[9] The respondents in our study are recruited randomly across the U.S. market. Due to the nature of our simple random sampling method, sampling weights are not used in our calculation of market shares (Pfeffermann 1993).

[10] We assume constant marginal shelf cost because there is no big difference in the sizes or weights of these products. The marginal shelf cost is defined per item rather than the number of items displayed. The reason is that the shelf space is a premium for the retailer in our study. As a result, the retailer exhibits only one item per SKU, with additional units behind the displayed unit.

[11] Details are available from authors upon request.

Figure 2 Market Scenario Development—After Entry of Design Alternative



product entry, (3) the manufacturers of the incumbent products changing their own wholesale prices as a competitive move, and (4) the retailer making an adjustment in retail prices for the revised product line.

For each product alternative, a market scenario is developed to solve for the Nash equilibrium wholesale and retail prices after the entry of that alternative. As described in Figure 2, our procedure for estimating the Nash equilibrium prices includes solving two optimization subproblems iteratively: the retailer profit maximization problem (second block in Figure 2) and the manufacturer profit maximization problem (third block in Figure 2).

Given an initial wholesale price of the new product alternative and current wholesale prices of the existing products, the retailer chooses the retail price for the new product and adjusts the retail prices of the existing products to maximize its category profit. The retailer's profit maximization is as per Equation (7). We use "tilde" here to highlight the variables that are affected by the introduction of the new product alternative, indicated by $(J+1)$ or "new."

$$\max_{\tilde{p}_1,\tilde{p}_2,\ldots,\tilde{p}_J,\tilde{p}_{\text{new}}} \widetilde{\pi}^r = \left\{\left(\sum_{j=1}^{J}[\widetilde{m}_j*(\tilde{p}_j-\widetilde{w}_j)]\right)+\widetilde{m}_{\text{new}}*(\tilde{p}_{\text{new}}-\widetilde{w}_{\text{new}})\right\}*S - sc*(J+1). \tag{7}$$

Using the FOCs for Equation (7) (similar to Equation (A1) in Appendix A), a set of new retail prices $(\tilde{p}_1, \tilde{p}_2, \ldots, \tilde{p}_J, \tilde{p}_{\text{new}})$ can be estimated after we express the market shares and the derivatives of market shares with respect to retail prices as functions of retail prices in the FOCs. Because the individual-level conjoint part-worths are embedded in these expressions, cannibalization among the products in the revised product line is accounted for via the part-worth utilities of these products.

All the manufacturers (including the incumbent manufacturers and the manufacturer of the new product) then adjust their wholesale prices to maximize their own profits. The manufacturers' profit maximization function is similar to the one described in Equation (4). Given the new set of retail prices and the marginal costs of the products, the adjusted wholesale prices $(\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_J, \widetilde{w}_{\text{new}})$ are calculated using the FOCs for the manufacturers.

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.

Each set of the retail and wholesale prices is solved using iterative algorithms, which are describe in detail in Appendix B. These algorithms are both based on gradient search methods. In order to apply these methods to our application, we need to ensure that the maximum obtained is the global maximum rather than a local maximum (Goldfeld and Quandt 1972, Greene 2000, Train 2003). In the context of manufacturers' profit maximization problem, it can be shown analytically that there exists a price equilibrium among the oligopolistic manufacturers (we highlight some of the key results of Caplin and Nalebuff 1991a, b in Appendix C). However, 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 (Hanson and Martin 1996, Schmalensee and Thisse 1988). Numerical proof of the concavity of a function is 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 semidefinite. Finally, we used different starting values of retail prices for several market scenarios and obtained highly similar estimates. 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.

Based on the equilibrium wholesale and retail 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.

4. Empirical Application

4.1. Consumer Preference Estimation

We applied our proposed framework to the development project of a new handheld power tool undertaken by a U.S. manufacturer. Teaming with our industrial partner, we identified an initial set of 15 product attributes. Next, we conducted exploratory research to narrow down the set of product attributes to six because they were considered to be the most critical by the end users. These six product attributes were: brand, price, amp rating, life of product, switch type, and actuator type (attribute levels are shown in Table 1). Using orthogonality as the design optimality criterion (Addelman 1962), we constructed 16 choice scenarios.[12] Each choice occasion included two alternative designs and a no-choice option. Two additional choice scenarios were constructed for validation purposes.

We obtained conjoint data from 249 participants, who were 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 U.S. market. A simple random-sampling method was used. A pre-experiment screen was done to ensure that the dominant retailer is the primary store for all of our participants. This retailer has approximately 57% of the market share for the distribution of this product category.

We estimated the individual-level conjoint part-worths using the hierarchical Bayesian conjoint model. We used 1,000 draws to construct the posterior estimates of each respondent with an initial burn-in period to ensure convergence. Table 1 gives the posterior estimates of the population mean and a measure of heterogeneity across individuals for each attribute level (Chung and Rao 2003). It is clear that there exists significant heterogeneity in preferences among the respondents, rendering the consideration of individual-level preferences important in our market share predictions for different market scenarios. The individual-level conjoint part-worths were used

Table 1 Estimation Results of Hierarchical Bayesian Conjoint Model

Parameter	Population posterior mean	Heterogeneity across individuals[a]
Brand A	0.838	2.323
Brand B	0.587	8.540
Brand C	−1.339	4.593
Own brand	−0.086	2.918
Price	−3.393	10.168
Amp rating(6)	−1.081	1.148
Amp rating(9)	0.980	1.561
Amp rating(12)	0.101	3.401
Life of product (80 hours)	−2.136	8.274
Life of product (120 hours)	−0.194	3.900
Life of product (150 hours)	2.330	2.739
Paddle switch	1.095	17.794
Top slider switch	0.367	14.793
Side slider switch	−1.919	14.251
Trigger switch	0.457	32.688
Actuator A	3.045	11.220
Actuator B	−3.045	11.220
No-choice	4.310	17.838

Note. Log-likelihood: −1,369.961, Chi-square: 6,070.116, Pseudo R^2: 0.690.

[a]These entries are the average of the sum of squares of the difference between the individual and the population posterior parameter estimates. This is similar to the measure in Chung and Rao (2003).

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.

The log-likelihood value of the estimated model and the pseudo R^2 value both indicate that the estimated model provides reasonable goodness of fit to the data. The results from our two holdout choice scenarios are given in Table 2, which also indicate a reasonable fit of our model. The first-choice hit rates are around 60% in both scenarios. The mean-absolute-error (MAE) measures are around 6%. Because both the predicted market shares and the observed market shares are realizations of the true unknowns, the minimum discrimination information statistic (MDI) (Kullback et al. 1962) is used to test whether the predicted and observed values are realizations from the same underlying multinomial distribution. Let $\{f_{1b}\}$ and $\{f_{2b}\}$ $(b = 1, 2, \ldots, S)$ represent the predicted frequencies from the conjoint part-worths and the observed frequencies indicated by respondents. The null hypothesis is that both streams of frequencies are from the same multinomial distribution. The expression for MDI is as follows:

$$\mathrm{MDI} = 2 * \sum_{a=1}^{2} \sum_{b=1}^{S} f_{ab} \ln\left[\frac{f_{ab}}{(f_{a\cdot} * f_{\cdot b}/f_{\cdot\cdot})}\right], \tag{8}$$

where $f_{a\cdot} = \sum_b f_{ab}$, $f_{\cdot b} = \sum_a f_{ab}$, and $f_{\cdot\cdot} = \sum_a \sum_b f_{ab}$.

It can be shown that MDI asymptotically follows a χ^2 distribution with $(S-1)$ degrees of freedom. Our

[12] We employ orthogonal conjoint design because it provides unbiased parameter estimates. We acknowledge that it may not be the most efficient design method (Huber and Zwerina 1996).

Table 2 Consumer Choice Validation

	Predicted share by conjoint utilities (%)	Observed share indicated by subjects (%)
Holdout scenario 1		
Product 1	42.73	34.14
Product 2	32.52	35.34
No-choice	24.75	30.52
First-choice hit rate	65.06%	
MAE	5.73%	
MDI	MDI = 4.200; p-value > 0.1	
Holdout scenario 2		
Product 3	15.29	10.44
Product 4	30.70	40.16
No-choice	54.01	49.40
First-choice hit rate	58.23%	
MAE	6.31%	
MDI	MDI = 5.956; p-value > 0.05	

calculation shows that the null hypothesis cannot be rejected under both holdout scenarios.

4.2. Market Specifics Before New Product Entry

Before the entry of the new product, the dominant retailer carried three products in the product category. The specifications of these three incumbent products are given in Table 3.

Based on the product specifications in Table 3, we estimated the market shares of the incumbent products using the conjoint part-worth estimates. Our estimation results suggested that 24.90% of the consumers in our sample would not purchase any of the existing products currently carried by the dominant retailer, which indicated a good opportunity for market expansion with the entry of the new product. To assess the face validity of our model, we compared the estimated market shares after the percentage of no-choice was factored out with alternative estimates of the market shares of these products obtained by our industrial partner (we call these the "observed market shares" in Table 3).[13] As Table 3 shows, the estimated market shares from our conjoint experiment are reasonably in line with the observed market share values, with the MAE being around 5%. The MDI statistic indicates that we cannot reject the null hypothesis that the estimated and the observed market shares are from the same underlying multinomial distribution. Table 3 also indicates 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.

Table 3 Specifications and Market Shares of Incumbent Products

	Product X	Product Y	Product Z	No-choice
Brand	Brand A	Brand B	Brand C	—
Price	\$99	\$129	\$79	—
Amp rating	9	12	6	—
Product life	120 hours	150 hours	80 hours	—
Switch type	Side slider	Paddle	Paddle	—
Actuator type	Actuator B	Actuator A	Actuator A	—
Estimated vs. observed market shares				
Estimated market share	14.18%	20.66%	40.26%	24.90%
Estimate market share (w/o no-choice)	18.88%	27.51%	53.61%	—
Observed market share	11.80%	30.10%	58.10%	—
MAE	4.72%			
MDI[a]	MDI = 4.845; p-value > 0.05			

[a] The sample size for observed market share is unknown. The MDI statistic assumes a sample size of 249 subjects.

Table 4 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		

The wholesale price estimates of the incumbent products and their marginal costs (based on the equations in Appendix A and the conjoint estimates) are shown in Table 4. In general, the retail margins are about three times the wholesale margins. This may be a reflection of the fact that the balance of power in the distribution channel is in favor of the retailer.

The face validity of our model estimates was assessed using the retail margin and marginal cost estimates provided by our industrial partner (who gathers these data on a regular basis using market intelligence). Our estimates were reasonably close to the actual market margins.[14] The estimates of the marginal costs of production were compared with the

[13] These market share data were obtained from the Power Tool Institute (PTI).

[14] An article in *Do It Yourself Retailing* (Bucksot and Eads 2004, p. 23) has a quote from a hardware store manager in Ohio to the effect 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.

cost estimates the engineers at our industrial partner arrived at using "reverse-engineering" (Ulrich and Pearson 1998). We found that the cost estimates provided by the engineers were also reasonably close to the estimates determined using our approach.

Next, we obtained information about the approximate market size in units of potential purchases from the 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 profit divided by the number of incumbent products, given the fact that the sizes of these products are very similar.[15] Finally, we calculated the retailer's category profit before new product entry. All these estimates are shown in Table 4.

4.3. After New Product Entry

Given the selected product attributes and their levels in our conjoint experiment, the focal manufacturer had a total of 72 design alternatives (three levels of amp rating, three levels of product life, four switch types, and two actuator types). Our estimates from the hierarchical Bayesian conjoint analysis indicated that about 80% of the respondents strongly preferred Actuator A to Actuator B, and the remaining 20% only slightly preferred Actuator B to Actuator A. Also, Actuator B is more expensive to produce than Actuator A. Therefore, the focal manufacturer decided to choose Actuator A in the design of the new product. Hence, the number of design alternatives considered was reduced to 36.

For each alternative, we calculated the Nash equilibrium wholesale and retail prices based on the iterative procedure (Figure 2) embedding the iterative algorithms (Appendix B). 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 was less than or equal to 0.01, we considered the iteration process to be converged. Adopting this convergence criterion led to essentially the same results as using tighter criteria, while greatly improving computational efficiency.

We adopted an exhaustive search 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 the design set of 36 alternatives. Despite the fact that an exhaustive search over the product design space is feasible for our application, a global optimization method (such as Genetic Algorithm) may be needed to improve the computation efficiency of a similar problem with a larger scale (Balakrishnan and Jacob 1996). Alternatively, the number of alternatives can be reduced through an evaluation of the population-level conjoint partworths. The attribute levels that are less preferred and cost more to produce can be eliminated prior to the construction of the design space.

We predicted the retailer category profit with the addition of each design alternative at the estimated equilibrium prices. This predicted category profit was compared to the category profit before the entry of the design alternative. Among the 36 design alternatives, 21 design alternatives did not increase retailer's category profit and thus were removed from further consideration. Table 5 provides the marginal cost of production, equilibrium retail and wholesale prices, and the status (retained or removed) for five design alternatives as an illustration of our analysis results. In this table, Alternatives 3, 7, and 29 did not increase the retailer's category profit at market equilibrium conditions. Therefore, they were eliminated from further consideration.

Our market scenario analysis provides several insights. For all of the 15 design alternatives that were predicted to increase the retailer's category profit, our market scenario analysis indicated that, at the market equilibrium conditions, the retailer's optimal behavior was to increase the retail prices charged for all the existing products. 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 the 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 offered at a lower price. The consumers must pay a price for such an improvement in the product assortment.

Another finding of our empirical analysis was that the profit-maximizing behavior of the incumbent in response to the new product entry is not always to

[15] This is a simplified way to calculate the marginal shelf cost. If additional data were available, a more sophisticated model of marginal cost could be used here to enhance the predictability of channel acceptance. We conducted sensitivity analysis to test the robustness of our optimal solution to this marginal shelf cost estimate. Our optimal solution remains valid as long as the actual marginal shelf cost is less than \$37.31 million. Given the fact that this is almost \$10 million higher than our estimated marginal shelf cost (\$26.4 million), we believe that our optimal solution is quite robust to the potential error in the marginal shelf cost estimate.

Table 5 Market Scenario Analysis—with Introduction of the New Product

Alternative number	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	Removed
7	105.79	97.48	130.16	79.75	131.60	78.46	109.95	56.46	113.87	Removed
10	54.73	100.36	132.88	82.35	81.65	78.04	109.10	54.77	60.92	Retained
16	83.85	100.05	134.96	89.73	116.56	72.98	106.05	56.01	91.54	Retained
29	85.76	98.99	133.09	81.02	111.32	77.65	110.40	54.96	91.48	Removed
Retail prices (before entry)		99.00	129.00	79.00		78.01	109.67	57.81	Wholesale prices (before entry)	

lower its own wholesale price. In Table 5, only the entry of Alternative 16 resulted in lower equilibrium wholesale prices of all the incumbent products. 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 Alternatives 3, 7, 10, and 29 in Table 5). This finding is consistent with Hauser and Shugan's (1983) analytical analysis of defensive marketing strategy. Depending on the distribution of the consumers' tastes and the market segment that the new product is targeting, a price increase could be optimal for the incumbents.

Among the 15 retained design alternatives, Alternative 10 provides the highest profit for the focal manufacturer. The specification of Alternative 10 is: amp rating (6), life of product: 80 hours, top slider switch, Actuator A, retail price at $81.65, and wholesale price at $60.92. When comparing this new product with the existing competitive products, this product seems to target the low end of the market and competes mostly with Product Z. Considering that the 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. In addition, 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 Products X, Y, and 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 the majority of its market share from Product Z. Also, because the new product satisfies some of the unmet consumer demand, the share of no purchase reduces from 24.9% (preentry) to 19.76% (postentry).

According to our analysis, this design alternative will create $ 8.99 million in profit for the focal manufacturer. 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 the current category profit.

4.4. Comparison to a Naïve Model

In this section, we benchmark our proposed model with a naïve model where the focal manufacturer selects the optimal new product without considering retailer acceptance, and the competing manufacturers and the retailer do not make any price adjustments in response to a new product entry. For all of the 36 design alternatives, the focal manufacturer charges a constant wholesale margin of $6.68 and assumes a constant retail margin of $20.5 (both specified at market average level). Given these assumptions, we estimated the market share of each new product alternative using the conjoint estimates. In this model, Alternative 17 provides the highest profit for the focal manufacturer. The specification of this design alternative (amp rating (9), life of product: 150 hours, top slider switch, Actuator A, retail price of $123.41) is clearly different from what our approach has suggested. More importantly, under the naïve model the chosen alternative will provide only $7.53 million in profit for the focal manufacturer, and the retailer category profit after entry will be only $67.03 million, in contrast to the profits of $8.99 million and $71.22 million, respectively, from our approach. Our approach promises a win-win situation for both parties in the channel relationship as compared to the naïve model.

5. Model Extensions

5.1. Replacement of Competitive Products in the Channel

In this model extension, we consider a situation in which the retailer considers replacing one existing product with the proposed new product, which might be the case if the shelf space is scarce. 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 (Alternative 10). We analyzed three market scenarios. In each of the market scenarios, one existing product

Table 6 **Market Scenario Analysis—Replacing One Existing Product with Alternative 10**

Product assortment	Equilibrium retail prices ($)			Equilibrium wholesale prices ($)			Retailer category Retailer category profit ($ in millions)
{X, Y, New}	98.44	130.77	80.29	78.67	109.75	61.85	51.97
{X, Z, New}	94.16	76.28	76.54	79.59	58.75	62.85	20.16
{Y, Z, New}	127.82	77.61	78.14	110.04	57.25	62.45	44.08

(Product X, Y, or Z) is replaced with Alternative 10 (Table 6).

At current level of marginal shelf cost, 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 extension of our model can also be very helpful because the focal manufacturer can use it to identify the competitive product to bid against when the dominant retailer calls for a product line review. The results in Table 6 also indicate that the retailer is no longer able to increase the retail prices of the existing products with the introduction of the new product because of the fixed category breadth.

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 from a single product. Equation (4) and Equation (A2) in Appendix A can be amended to incorporate this change. The amended FOCs can be combined with the competing manufacturers' FOCs to solve for the profit-maximizing wholesale prices (similar to the procedure described in Block 3 of Figure 2). 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 the Optimal Solution to Potential Reactions from Competing Retailers

Assume that upon the addition of the optimal new product (Alternative 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 (9). We use "$*$" to represent the equilibrium prices calculated from our model.

$$m_j = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(\mathbf{x}_j'\hat{\beta}_{ix}+p_j^*\hat{\beta}_{ip})}{\sum_{j'=1}^{J+1}[\exp(\mathbf{x}_{j'}'\hat{\beta}_{ix}+p_{j'}^*\hat{\beta}_{ip})]+\exp(\hat{a}_i+\hat{\beta}_{ip}\Delta p)} \quad j=1,\ldots,J+1, \quad (9)$$

where $\Delta p =$ the average retail price decrease of the competing retailers' offerings.

If Δp is large, the dominant retailer will lose a big portion of its market to the competing retailers and adding Alternative 10 may make the retailer worse off. 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. There is a value of Δp that makes the dominant retailer indifferent between adding this new product and not adding it, and this value can be determined algebraically. For our application, this breakeven value of Δp is $-\$5.40$. 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, as long as the competing retailers respond by an average price cut of less than \$5.40. Note that our sensitivity analysis is also conservative because, in reality, it is not likely that all consumers will have full price information on 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 a price decrease from the competing retailers (Wernerfelt 1991).

6. Conclusions

We have proposed an application framework to help manufacturers in specific institutional settings to directly account for the acceptance criteria of dominant retailers in introducing optimal new products. While this has been recognized as an important problem in extant literature, our paper is the first effort in tackling this important issue. Given that new products have intense competition in making it onto retailers' shelves (Bounds 2006), our framework could have a significant impact on manufacturers' new product introduction decisions. This method melds 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 in developing market forecasts of equilibrium market shares and profits associated with different design alternatives. While our framework is specific to the institutional setting, it provides a useful illustration for developing analogous applications to other settings. We contribute to the literature by choosing and justifying the normative models and empirical methodologies appropriate for the application, given our knowledge of the institutional setting.[16] Our integrated framework provides a rigorous, yet practical, solution to the manufacturer's problem. The strength of the framework is that it is not overly constrained by the specific preference elicitation method (logit, probit, or random coefficient logit models), and the framework can guide the application in other institutional settings.

Within the specific setting we consider, our approach can be the basis for a decision support system (DSS) to aid managers in selecting new product designs. The market scenarios can be useful in targeting a specific competitor product for replacement in the retailer's assortment when retailers call for a product line review (to which powerful retailers are increasingly resorting). In addition, the DSS can help manufacturers of the new products in supporting their negotiations for market entry with the dominant retailers. Furthermore, the DSS can be used as a category management tool to educate the retailers regarding how to make price adjustments in its product line in response to the introduction of a new product. Thus, manufacturers adopting this application framework 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.

Future research can extend our approach to analyze a variety of other problems. One extension could be to examine the optimal product positioning and pricing strategy in channels with two-part pricing, quantity discounts, or slotting allowances. Under such institutional settings, a combination of category management and channel coordination should be incorporated into 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, a store-choice model could be added to our model to allow derivation of the optimal new product positioning and pricing strategy under retail equilibrium as well as manufacturer equilibrium. Furthermore, even though a pure-strategy equilibrium does not generally exist for the case of uniform pricing strategy (Anderson et al. 1992), alternative pricing structures and functional forms of consumer demand may be used to derive a desirable long-term pure-strategy equilibrium in both product positioning and pricing. Finally, a global optimization method (such as Genetic Algorithm), with the objective function being the focal manufacturer's profit maximization and the retailer's acceptance being a constraint, could be used to improve the computational efficiency of a larger-scale problem under similar settings.

[16] This is similar in spirit to the recent marketing literature focusing on applying models for practical, large-scale problems (e.g., Divakar et al. 2005, Roberts et al. 2005, Sinha et al. 2005).

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Appendix A. Estimating Wholesale Prices and Marginal Costs of Incumbent Products before Entry
In the manufacturer Stackelberg model, the retailer's pricing decisions are a function of wholesale prices, which are determined by the manufacturers. Taking the wholesale prices as given, the retailer's FOCs for Equation (3) are:

$$\frac{\partial \pi^r}{\partial p_j} = m_j + \sum_{j'=1}^{J}\left[(p_{j'} - w_{j'})\frac{\partial m_{j'}}{\partial p_j}\right] = 0 \quad j = 1, \ldots, J. \tag{A1}$$

In Equation (A1), the retail prices of the incumbent products are observable. In addition, we can obtain the market share estimates of these products $(\widehat{m}_1, \widehat{m}_2, \ldots, \widehat{m}_J)$ from the conjoint analysis. Also, given the multinomial logit formation in Equation (2), the derivatives of market shares (own and across) with respect to retail prices can be calculated. Therefore, we can calculate the wholesale prices $(w_1, w_2, \ldots, w_J)$ of the incumbent products based on Equation (A1). Accordingly, the retail category profit before new product entry can also be estimated.

On the manufacturer side, each incumbent manufacturer chooses a wholesale price to maximize its own profit. The FOCs for Equation (4) are:

$$\frac{\partial \pi^m}{\partial w_j} = m_j + (w_j - c_j)\sum_{j'=1}^{J}\frac{\partial m_j}{\partial p_{j'}}\frac{\partial p_{j'}}{\partial w_j} = 0 \quad j = 1, \ldots, J. \tag{A2}$$

The FOCs in Equation (A2) imply 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 FOCs (Equation (A1)), the retailer's pricing responses are a function of the wholesale prices. Therefore, after taking derivatives of the retail prices with respect to the wholesale prices in Equation (A1) and reorganizing the results, we have the following:

$$\left(\frac{\partial p_1}{\partial w_j}, \frac{\partial p_2}{\partial w_j}, \ldots, \frac{\partial p_J}{\partial w_j}\right)' = \left(\frac{\partial m_j}{\partial p_1}, \frac{\partial m_j}{\partial p_2}, \ldots, \frac{\partial m_j}{\partial p_J}\right)'(G^{-1})' \quad j = 1, \ldots, J, \tag{A3}$$

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

$$g_{jk} = \frac{\partial m_j}{\partial p_k} + \frac{\partial m_k}{\partial p_j} + \sum_{j'=1}^{J}\left[(p_{j'} - w_{j'})\frac{\partial^2 m_{j'}}{\partial p_j \partial p_k}\right] \quad j = 1, \ldots, J. \tag{A4}$$

Substituting the above expressions for $\partial p_{j'}/\partial w_j$ into Equation (A2), we can calculate the marginal cost of production for each existing competitive product using the conjoint estimates and the estimated wholesale prices $(\widehat{w}_1, \widehat{w}_2, \ldots, \widehat{w}_J)$.

Appendix B. Iterative Algorithm of Solving Equilibrium Prices After Entry

We start with solving profit-maximizing retail prices (second block in Figure 2). Let $\tilde{p}$ denote the vector of retail prices to be solved. Let g denote the gradient at $\tilde{p}$ (i.e., $g = \partial\widetilde{\pi}^r/\partial\tilde{p}$). 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., $\widetilde{\pi}^r|_{\tilde{p}_{t+1}} > \widetilde{\pi}^r|_{\tilde{p}_t}$), move to $\tilde{p}_{t+1}$, and go to step (c). Otherwise, reduce the step size λ to 1/2, 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 2) 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.

Appendix C. Price Equilibrium Among Oligopolistic Manufacturers

We outline the key results of Caplin and Nalebuff (1991a), which prove the existence of price equilibrium among the oligopolistic manufacturers and show how the proof applies to our case, as well as to other functional forms of preference elicitation models. Some of the notation in the original proof is changed to be consistent with the notation we use in this paper.

Theorem (Caplin and Nalebuff 1991a). *Under* A1 *and* A2, *for any J firms and arbitrary products $\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2, \ldots, \bar{\mathbf{x}}_J$, there exists a pure-strategy Bertrand-Nash equilibrium.*

Assumption 1 (A1). *Preferences are linear in B_i:*

$$U(B_i, \bar{\mathbf{x}}_j) = \sum_{r=1}^{R} \beta_{ir} t(x_{rj}), \tag{C1}$$

where each individual i evaluates a product j by a weighted sum of the benefits provided by the product characteristics. These benefits are determined by a function t, which maps the R-dimensions of the product characteristics into one dimension: consumer utility.

Assumption 2 (A2). *The probability density of consumers' utility parameters is $\rho = (-1/(R+1))$-concave on an R-dimensional space* (*this concavity definition is discussed in detail in Caplin and Nalebuff* 1991*a*, *b*).

In our paper, the game setup among the oligopolistic manufacturers is Bertrand-Nash, in which each manufacturer chooses a wholesale price w_j to maximize its own profit. The utility function for an individual consumer can be expressed as:

$$U(B_i, \bar{\mathbf{x}}_j) = \beta_{io}\mathbf{x}_j^o + \beta_{iu}\mathbf{x}_j^u, \tag{C2}$$

where $\mathbf{x}_j^o$ are the observable product characteristics and $\mathbf{x}_j^u$ are the unobservable product characteristics. In particular, the utility function takes a simpler form in which $\mathbf{x}_j^u = 1$ and β_{iu} represents the random component of the utility.

From the standpoint of the manufacturer, retail price can be decomposed into a wholesale price and a retail margin component, $p_j = w_j + rm_j$, and the retail margin can be thought of as another attribute in the demand function facing the manufacturer. The vector of the observable product characteristics thus takes the form of $\mathbf{x}_j^o = (\bar{\mathbf{x}}_j, rm_j, w_j)$ with $\bar{\mathbf{x}}_j$ representing the non price attributes, rm_j denoting the retail margin imposed by the retailer, and w_j being the wholesale price chosen by the manufacturer. Also, β_{io} in Equation (C2) is normally distributed across the population and β_{iu} follows a double exponential distribution as required by a random coefficients logit model. Given this, the derived demand function facing each manufacturer follows the random coefficients logit model.

As discussed in Example 3.2 in Caplin and Nalebuff (1991a), the utility function specified under the random coefficients logit model satisfies both assumptions listed above. First, given that β_{io}, β_{iu} enter the utility function linearly, A1 is satisfied. Second, the $\rho = (-1/(R+1))$-concave property is a weaker condition than the log-concavity property of the density distribution. Both the normal distribution and the double exponential distribution are log-concave. The joint distribution of (β_{io}, β_{iu}) is the product of two log-concave density distributions, which is also log-concave (see more discussions in Caplin and Nalebuff 1991b). Therefore, the utility function specified under the random coefficients logit model satisfies A2.

The manufacturer sets prices conditional on the anticipated actions of the retailer and the competing manufacturers. Following Caplin and Nalebuff (1991a), the demand function facing the manufacturer conditional on these decisions is quasi-concave in w_j if A1 and A2 are satisfied. Application of Kakutani's fixed-point theorem then establishes the existence of a fixed point. Such a fixed point is a Bertrand Nash equilibrium. Caplin and Nalebuff (1991a) have also shown that there exists a *unique* pure-strategy Bertrand-Nash equilibrium for the case of the logit model, and that the above result covers most models of consumer preference elicitation using logit, probit, or random coefficients logit formulation.

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