Augmenting Conjoint Analysis to Estimate Consumer Reservation Price

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Consumer reservation price is a key concept in marketing and economics. Theoretically, this concept has been instrumental in studying consumer purchase decisions, competitive pricing strategies, and welfare economics. Managerially, knowledge of consumer reservation prices is critical for implementing many pricing tactics such as bundling, target promotions, nonlinear pricing, and one-to-one pricing, and for assessing the impact of marketing strategy on demand. Despite the practical and theoretical importance of this concept, its measurement at the individual level in a practical setting proves elusive.

We propose a conjoint-based approach to estimate consumer-level reservation prices. This approach integrates the preference estimation of traditional conjoint with the economic theory of consumer choice. This integration augments the capability of traditional conjoint such that consumers' reservation prices for a product can be derived directly from the individual-level estimates of conjoint coefficients. With this augmentation, we can model a consumer's decision of not only which product to buy, but also whether to buy at all in a category. Thus, we can simulate simultaneously three effects that a change in price or the introduction of a new product may generate in a market: the customer switching effect, the cannibalization effect, and the market expansion effect. We show in a pilot application how this approach can aid product and pricing decisions. We also demonstrate the predictive validity of our approach using data from a commercial study of automobile batteries.
(*Reservation Price; Conjoint Analysis; Pricing Strategy; Product Stratgy*)

1. Introduction

In making pricing and product decisions, a firm needs to gauge their effects not only on product demand, but also on market demand. Consider, for instance, the case in which a computer company, say Compaq, is deciding whether to enter the market of notebook computers with a low-end product at a low price to pursue a penetration strategy, or with a high-end product at a high price to pursue a skimming strategy, or with both high-end and low-end products to pursue a product line strategy. To make such a decision, Compaq needs to consider how its product or products may take customers away from its competition, say Dell, i.e. "the customer switching effect." It must also assess how its high-end (low-end) product may suffer in sales because of its low-end (high-end) product, or "the cannibalization effect," and how its product or products may draw more customers into the market because of better functionality or affordability, or "the market expansion effect." In this paper, we propose a simple, conjoint-based approach to estimate all these three effects and further illustrate how this approach can facilitate such complex product and pricing decisions.

From the perspective of the standard economic theory of consumer choice, the key to assessing all these effects in a single model is knowledge of consumers' reservation prices for current and new product

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offerings in a category. To continue with our notebook computer example, if a market researcher at Compaq knows how much each of the target consumers is willing to pay for its high-end and low-end products and for each of the Dell's products, she can then determine who will switch away from Dell to purchase a Compaq notebook (the customer switching effect), to what extent Compaq's one product may compete with the other (the cannibalization effect), and how category sales may expand (the market expansion effect) as a result of Compaq's new offering. Cannibalization (switching) results when consumers derive more surplus from a new offering than from the company's (competitor's) existing product. Market expansion results when noncategory buyers now derive positive surplus from a new offering.

The practical importance of estimating consumer reservation prices is not, of course, limited to assessing these three demand effects. Knowledge of consumer reservation prices aids market researchers in implementing many pricing tactics such as bundling (Jedidi et al. 2002), target promotions, nonlinear pricing, and one-to-one pricing (Shaffer and Zhang 1995, 2000). For instance, with no information on individual-level reservation prices, one-to-one pricing is largely a theoretical curiosity or an exercise of guesswork. Furthermore, such knowledge bridges the gap between economic theories and marketing practice and enables researchers to study a host of other issues related to competitive interactions, policy evaluations, welfare economics, and brand value. The importance of the reservation price concept is also shared by managers. In a survey conducted by Anderson et al. (1993), managers consider consumer reservation prices as "the cornerstone of marketing strategy," particularly in the areas of product development, value audits, and competitive strategy.

Despite the practical and theoretical importance of the concept of consumer reservation price, its measurement at the individual level in a practical setting proves elusive. Researchers most frequently elicit such information directly from consumers, although stated consumer reservation prices are known to be biased downward (Monroe 1990). Kohli and Mahajan (1991) first propose the use of conjoint analysis to estimate a consumer's willingness to pay for a product. The reservation price they estimate measures, however, the differentiation value of a product relative to the status quo product. This definition of reservation price implies that all consumers are category buyers and hence it assumes away any market expansion effect. In this paper, we follow Kohli and Mahajan's approach to derive individual-level reservation prices directly from the estimates of conjoint coefficients. However, we depart from Kohli and Mahajan (1991) in two ways. First, we adopt the standard definition of consumer reservation price in economics. Second, we dismiss the assumption of unconditional category purchase.

Our approach integrates the preference estimation from conjoint with the standard economic theory of consumer utility maximization. Using the economic theory of consumer choice, namely consumers maximizing their utility by choosing a consumption bundle from their respective feasible consumption set, we show that a consumer's reservation price for a product can be generated from a rather simple transformation of attribute utilities estimated through conjoint. With this transformation, we can model a consumer's decision of not only which product to buy in a category of interest, but also whether to buy at all in that category. As a result, we can simultaneously simulate all three effects that a change in price or the introduction of a new product may generate in a market: the customer switching effect, the cannibalization effect, and the market expansion effect. Besides, we can do so while preserving the conceptual and operational simplicity of conjoint, which has contributed to its enduring popularity.[1]

As commonly used in practice, conjoint analysis captures only the customer switching and cannibalization effects. Many scholars have advanced the conjoint approach in the past to enable researchers to capture the market expansion effect. Louviere and Woodworth (1983) and later Desarbo et al. (1995) allow for a "no-choice" option in the conjoint design

[1] For survey articles of conjoint applications, see Green and Srinivasan (1990), Wittink and Cattin (1989), Anderson et al. (1993), and Wittink and Bergestuen (1999). For some specific conjoint applications, see Green and Wind (1975), Mahajan et al. (1982), and Page and Rosenbaum (1987).

to capture the market expansion effect. Mason (1990) suggests merging a preference model (conjoint) with a demand model based on the concept of the total product class attraction. More recently, Jedidi et al. (1996) model the market expansion effect by letting consumer consideration sets depend on the product offerings in a category. We show that our approach offers the distinct advantages of taking decision making from the "choice" arena to the "value" arena by estimating the reservation price at the individual level. However, it is reassuring, as we will demonstrate, that our approach does as well as a Tobit-based model such as that of Jedidi et al. (1996) in predicting consumer choices.

In the rest of the paper, we first discuss the concept of consumer reservation price and show how it can be estimated through conjoint analysis. Then, we illustrate how our approach can facilitate complex product and price decisions using a pilot application and demonstrate the predictive validity of our approach using data from a commercial study of automobile batteries. Finally, we conclude with some remarks on the advantages and limitations of our approach.

2. Consumption Utility and Reservation Price

A consumer's reservation price for a specific product is simply the price at which the consumer is indifferent between buying and not buying the product, given the consumption alternatives available to the consumer. Formally, let $\mathcal{P}$ denote a product profile, where $\mathcal{P} \in [\mathbf{P}^1, \ldots, \mathbf{P}^J]$. Assume that the utility function of consumer i is given by $U_i(\mathcal{P}, y_i)$, where y_i denotes the composite good consisting of all other goods the consumer purchases, measured in some individual-specific basket. Since each individual consumer has a different buying pattern, we allow the price of the composite good to differ across consumers and denote it by p_i^y. We further assume that consumer i has income m_i and consumes only one unit of the product in question. Therefore, the budget constraint facing consumer i is $p_i^y y_i + p = m_i$, where $p \in (p^1, \ldots, p^J)$ is the price the consumer pays to get product $\mathcal{P}$. This means that consumer i's indirect utility function is given by $U_i(\mathcal{P}, (m_i - p)/p_i^y)$ if the product $\mathcal{P}$ is purchased and by $U_i(0, m_i/p_i^y)$ if it is not. Then, by definition, consumer i's reservation price for product profile $\mathcal{P}$, denoted by $r_i(\mathcal{P})$, is implicitly given by

$$U_i\left(\mathcal{P}, \frac{m_i - r_i(\mathcal{P})}{p_i^y}\right) - U_i\left(0, \frac{m_i}{p_i^y}\right) \equiv 0. \tag{1}$$

This definition of $r_i(\mathcal{P})$ in Equation (1) is quite different from that of Kohli and Mahajan (1991). They define reservation price for a product as the maximum price the consumer is willing to pay to switch away from the most preferred choice in her evoked set to the product in question. Thus, a consumer's reservation price for a product depends not only on the additional value the product provides, but also on how much the consumer pays for her most preferred choice. This definition, based on the differentiation value of a product, facilitates their discussion about the market share impact of a new product's price, one of the main thrusts of their paper. However, by explicitly assuming the existence of a status quo product for each consumer, their approach cannot assess whether the product and pricing decisions by firms can expand or contract a market, an issue of importance in this paper.

Our definition is a conventional one. It captures a consumer's valuation of a product's nonprice attributes given the consumption opportunities elsewhere and the budget constraint she faces. As we show in Appendix A, with some quite general assumptions about consumer utility function, $r_i(\mathcal{P})$ always exists such that for any $p \le r_i(\mathcal{P})$, the consumer is better off purchasing the product $\mathcal{P}$. Otherwise, the consumer will not. Therefore, $r_i(\mathcal{P})$ is the maximum price the consumer is willing to pay for the product. This definition naturally allows us to determine whether a consumer purchases a product in question. Furthermore, with some additional restrictions on a consumer's utility function, a consumer's reservation price thus defined also allows us to examine the market share impact of a product's price in a straightforward manner. Specifically, if a consumer's utility function is of quasi-linear form, i.e., $U_i(\mathcal{P}, y_i) = u_i(\mathcal{P}) + \alpha y_i$, where $\alpha > 0$ is a scaling factor, a utility-maximizing consumer will only need to know her reservation prices for the product offerings and the corresponding prices for these products to make the optimal choice. For instance, if consumer i faces two alternative choices in the same product category, say some $\mathcal{P}$ and $\mathbf{P}^l (\mathcal{P} \neq \mathbf{P}^l)$, she will choose product $\mathcal{P}$ if $r_i(\mathcal{P}) - p \geq r_i(\mathbf{P}^l) - p^l$ and $r_i(\mathcal{P}) \geq p$. In other words, consumer i will purchase product $\mathcal{P}$, given that product $\mathbf{P}^l$ is also available, if consuming product $\mathcal{P}$ gives her more surplus and if her reservation price for the product is higher than the price she has to pay (see Appendix B for a proof).

In general, facing $j \leq J$ available choices in a product category, consumer i with a quasilinear utility function will purchase a product, say $\mathcal{P}$, in the category if the following two conditions are satisfied:

$$r_i(\mathcal{P}) - p \geq \max\{r_i(\mathbf{P}^1) - p^1, \ldots, r_i(\mathbf{P}^J) - p^J\}, \quad (2)$$

$$r_i(\mathcal{P}) \geq p. \quad (3)$$

She will forego purchase in the category if

$$\max\{r_i(\mathbf{P}^1) - p^1, \ldots, r_i(\mathbf{P}^J) - p^J\} < 0. \quad (4)$$

Equations (2)–(4) fully characterize a consumer's whether-to-buy and what-to-buy decisions.

3. Conjoint Analysis and Reservation Price

To estimate consumer reservation prices, it is natural to think of conjoint analysis, as the utility function specified for such analysis is quasilinear. In this section, we show how conjoint analysis can be augmented for that purpose.

Substituting in the individual-specific budget constraint, a quasi-linear utility function can be written as

$$U_i(\mathcal{P}) = u_i(\mathcal{P}) + \alpha \frac{m_i - p}{p_i^y}. \quad (5)$$

As in multiattribute utility models, we assume that the utility a consumer derives from consuming a product is the sum of utilities for its attributes or features. Specifically, we assume

$$u_i(\mathcal{P}) = \sum_{k=1}^{N} u_{ik}(\mathcal{P}) = \sum_{k=1}^{N} \beta_{ik} A_k, \quad (6)$$

where $u_{ik}(\mathcal{P}) = \beta_{ik} A_k$ is consumer i's utility from non-price attribute k of product profile $\mathcal{P}$, where $k = 1, 2, \ldots, N$, and A_k is the value of the kth non-price attribute. Furthermore, let $\beta_{i0} = \alpha(m_i/p_i^y)$ and $\beta_{ip} = (\alpha/p_i^y)$. Then, Equation (5) can be written as

$$U_i(\mathcal{P}) = \beta_{i0} + \sum_{k=1}^{N} \beta_{ik} A_k - \beta_{ip} p. \quad (7)$$

Using the definition in Equation (1), it is straightforward to show that under this specification, a consumer's reservation price for product profile $\mathcal{P}$ is given by

$$r_i(\mathcal{P}) = \frac{1}{\beta_{ip}} \sum_{k=1}^{N} \beta_{ik} A_k. \quad (8)$$

Note that $r_i(\mathcal{P})$ does not depend on the intercept term β_{i0}.

As Equation (7) resembles the common specification of conjoint analysis, it is tempting to use a conjoint design to estimate the parameters in Equation (7) directly and then use Equation (8) to compute a consumer's reservation price. However, note that each product attribute in Equation (7) is measured by its actual level, rather than by an indicator variable as is commonly the case in conjoint analysis. We therefore need to transform Equation (7) further before we can use a conjoint design to estimate it.

Assume for now that each attribute has only two levels of realization, say $\underline{A}_k$ and $\overline{A}_k$ ($\underline{A}_k < \overline{A}_k$) for non-price attributes and $\underline{p}$ and $\bar{p}$ ($\underline{p} < \bar{p}$) for price. We use $\mathbf{P}^l$ to denote the product profile that has the lowest level of each attribute among all possible product choices, and the expression for $U_i(\mathbf{P}^l)$ can be found using Equation (7). By taking the difference between $U_i(\mathcal{P})$ and $U_i(\mathbf{P}^l)$ and applying some simple arithmetic manipulations, we have

$$U_i(\mathcal{P}) = \beta_{i0}^c + \sum_{k=1}^{N} \beta_{ik}^c d_k - \beta_{ip}^c d_p, \quad (9)$$

where the superscript c indicates conjoint parameters defined as

$$\beta_{i0}^c = U_i(\mathbf{P}^l), \quad \beta_{ik}^c = \beta_{ik} \Delta A_k, \quad \beta_{ip}^c = \beta_{ip} \Delta p, \quad (10)$$

$$d_k = \frac{A_k - \underline{A}_k}{\Delta A_k}, \quad \text{and} \quad d_p = \frac{p - \underline{p}}{\Delta p}. \quad (11)$$

Note that when each attribute has only two levels of realization in a conjoint design, d_k and d_p are actually dummy variables with a value of either 1 or 0. Equation (9) can be estimated as

$$U_i(\mathcal{P}) = \beta^c_{i0} + \sum_{k=1}^{N} \beta^c_{ik} d_k - \beta^c_{ip} d_p + \epsilon_i. \qquad (12)$$

A standard conjoint design can be used to estimate this equation. Once the estimates of β^c_{i0}, β^c_{ik}, and β^c_{ip} are obtained, we can easily use Equations (10)–(11) to find the corresponding utility parameters and derive the estimate of a consumer's reservation price for product $\mathcal{P}$ by using Equation (8). We have

$$r_i(\mathcal{P}) = \frac{\Delta p}{\beta^c_{ip}} \left(\sum_{k=1}^{N} \frac{\beta^c_{ik}}{\Delta A_k} A_k \right). \qquad (13)$$

Equation (13) has a nice interpretation: Δp is the change in price from the base level and β^c_{ip} is the corresponding change in consumer i's utility. Therefore, $\Delta p/\beta^c_{ip}$ is the dollar value that the consumer implicitly assigns to each unit of her utility ($ per utile). In other words, it is the "exchange rate" between utility and money for the consumer. Similarly, $\beta^c_{ik}/\Delta A_k$ indicates the worth of each unit of attribute k in utiles (e.g., utiles per GB hard drive). Since product $\mathcal{P}$ has A_k as its level of attribute k, $(\beta^c_{ik}/\Delta A_k)A_k$ is the utility consumer i derives from attribute k. Therefore, the summation over all attributes for product $\mathcal{P}$, excluding price, simply yields the total utility the consumer derives from all nonprice attributes of product $\mathcal{P}$. Thus, this total utility multiplied by the revealed exchange rate between utility and money for the consumer in Equation (13) gives the total dollar value the consumer places on product $\mathcal{P}$, which ought to be consumer i's reservation price for the product. Equation (13) is also empirically appealing. From this equation we note that all else being equal, more price-sensitive consumers, or those with a larger β^c_{ip}, will have smaller reservation prices. A larger magnitude of positive response to any nonprice attribute will, however, increase a consumer's reservation price.

As in Equation (8), note that a consumer's reservation price in Equation (13) does not depend on the intercept term β^c_{i0}. This feature reflects the fact that β^c_{i0} conveys no preference information and hence should not play any role in a consumer's reservation price. This is true because β^c_{i0} does not survive a monotonic transformation of Equation (12). To see this, apply the following monotonic transformation to Equation (12): Multiply the right side of the equation by 1 and then subtract β^c_{i0} from the resulting expression. We see that β^c_{i0} disappears from the resulting utility function that represents the same preference ordering.[2]

From an empirical perspective this feature is quite valuable, as it removes the "scale effect" from our estimation of consumer reservation prices and creates a level playing field for interpersonal comparisons. The scale effect arises from the fact that subjects performing conjoint tasks may have different "internal scales" in measuring their utility. Because of these differences, a consumer who uses a large (small) number to convey her utility from a product may or may not be willing to pay a high (low) price for the product. Thus, no presumption should be made with regard to the relationship between a consumer's representation of her utility on the high or low end of an external scale and her willingness to pay for a product. Interestingly, our derivations show, as we can see from Equation (10), that this "scale effect" is indicated, in the case of two attribute levels, by a consumer's utility from consuming the product with the lowest level of all nonprice attributes.

With a consumer's reservation price for a product estimated, we can use Conditions (2)–(4) to predict whether a consumer will buy in a category and which product she will buy when different alternatives are present. However, we need to clarify three issues before we proceed to empirical applications. First, in many marketing applications a product attribute may simply be a nominal variable such as brand name. How should the transformation be carried out in this case? Second, the linearity of attribute utilities that we adopt through Equation (6) implicitly assumes that an attribute does not have any meaningful utility only when the measurement of that attribute is zero. However, in practical applications it may be desirable to allow a threshold value such that an attribute does not generate any utility unless it exceeds the threshold. For instance, in the case of cellular phones a consumer may attach zero value to "stand-by time" if it

[2] For details, see Varian (1992, p. 95).

is less than two hours. How should Equation (13) be adjusted to accommodate this threshold value? Third, a product attribute can have more than two levels of realization. How should the transformation be carried out then, especially when the attribute of price has multiple levels?

The answer to the first question is not difficult to find. As in conjoint analysis, a nominal variable such as brand name can enter in Equation (6) only as a dummy variable indicating its presence or absence. This means that if the kth attribute is a nominal variable, we must have $\Delta A_k = 1$ so that $\beta_{ik}^c = \beta_{ik}$ as one would expect. However, our approach to reservation prices is constructive. To generate a meaningful estimation of the value that a consumer places on an attribute, one needs to code a nominal variable in a way that can generate a meaningful measurement of the total, rather than relative, attribute utility from the variable. The key to coding a nominal variable is to select a proper reference point or a default. In the case of brand name, for instance, a default could be a *generic* brand from whose name alone consumers derive no meaningful utility.[3] Obviously, the choice of the default in this case does not affect comparisons among different brands, as the generic brand is now the common base for comparison.

Admittedly, for some other nominal attributes, it may not always be straightforward to find such a default. However, even in that case, we do not face any insurmountable obstacle in estimating consumer reservation prices. In §5, we show how one can use a Tobit approach to resolve such a problem. The catch is that a "no-buy" option is required in the conjoint design.

To address the second question, we note that the utility from an attribute that has a value below a threshold, say T_k, is zero. Yet, Equation (13) uses the absolute level A_k in computing a consumer's reservation price, which will obviously inflate the estimate of a consumer's willingness to pay. However, this problem can be easily corrected in theory by subtracting the threshold value from A_k in Equation (13), i.e., $A_k - T_k$. Mathematically, this operation is equivalent to relocating the origin in the attribute space and Equation (13) is then modified as

$$r_i(\mathcal{P}) = \frac{\Delta p}{\beta_{ip}^c}\left(\sum_{k=1}^{N} \frac{\beta_{ik}^c}{\Delta A_k} A_k\right) - \frac{\Delta p}{\beta_{ip}^c}\left(\sum_{k=1}^{N} \frac{\beta_{ik}^c}{\Delta A_k} T_k\right). \qquad (14)$$

The first term in Equation (14) is the gross value a consumer places on product $\mathcal{P}$. The second term is the implied value of dead-weight attributes, which cannot be appropriated by a firm. Note that the second term is constant for all $\mathcal{P} \in (P^1, P^2, \ldots, P^J)$.

In practice, the estimation of the thresholds can proceed in three possible ways. First, as in hybrid conjoint, the attribute thresholds T_ks can be directly elicited from subjects. Second, multiple levels of an attribute can be included in the conjoint design to identify the "jump" in part-worth estimates so that each T_k can be identified. Finally, as we will show in §5, if estimating individual T_ks is not critical, the second term of Equation (14) can be estimated as one parameter through a Tobit model. This option is possible only if each respondent's preferences are left-censored (i.e., we observe preferences only for the profiles that a respondent would consider buying).

When a product attribute has multiple levels, we can allow nonlinear effects of the attribute on a consumer's utility. In this case, the variable transformation is a bit more involved conceptually, but straightforward operationally. In Appendix C, we show that an attribute with three levels of realization, say attribute k, lends itself very well to conjoint estimation. What one needs to do is to specify two dummy variables for the attribute using the middle level as the default. Then, the attribute can be written as

$$u_{ik}(\mathcal{P}) = \underline{\beta}_{ik}^c \underline{d}_k + \bar{\beta}_{ik}^c \bar{d}_k + \underline{\beta}_{ik} \widetilde{A}_k, \qquad (15)$$

where $\underline{d}_k = 1$ if the kth attribute is at the lowest level and $\underline{d}_k = 0$ if otherwise, and $\bar{d}_k = 1$ if the kth attribute is at the highest level and $\bar{d}_k = 0$ if otherwise. Then

[3] Note here that this way of coding a brand name does not imply that consumers will have a zero reservation price for the "generic" product. It merely means that consumers derive zero value from the generic brand name per se. From (13), we can readily see that a consumer's reservation price for a product, whether it is a branded or generic product, is positive as long as the consumer derives sufficient positive utilities from all of the product's attributes. Thus, the reservation price of a generic product will be a function of the nonbrand attributes only.

we can redefine $U_i(\mathbf{P}^l)$ as consumer i's utility from the product profile that has the lowest level of each two-level attribute and the intermediate level of each three-level attribute. By doing so, we can simply substitute in the first two terms of Equation (15) for any attribute that has three levels of realization in Equation (12), as the last term in Equation (15) is canceled out when we take the difference between $U_i(\mathcal{P})$ and $U_i(\mathbf{P}^l)$. Then, $\underline{\beta}^c_{ik}$ and $\bar{\beta}^c_{ik}$ can be estimated through conjoint analysis, which will in turn allow us to find the value that a consumer places on the attribute through a set of transformation formulas detailed in Appendix C. This kind of transformation can also be done, as we show in Appendix D, to deal with attributes that have four or more levels.

When price has three levels of realization, the transformation is not as straightforward as it may seem. If we were to follow the common practice of conjoint specifications, we can let price enter Equation (7) arbitrarily as a piecewise linear function $\delta_1(p)\beta_{ip}p + \delta_2(p)\tilde{\beta}_{ip}p$, instead of $\beta_{ip}p$, where

$$\delta_1(p) = \begin{cases} 1 & \text{if } p \in [\underline{p}, \tilde{p}] \\ 0 & \text{if otherwise} \end{cases}$$

$$\delta_2(p) = \begin{cases} 1 & \text{if } p \in (\tilde{p}, \bar{p}] \\ 0 & \text{if otherwise.} \end{cases} \tag{16}$$

Then, the transformation can proceed in the same way as a nonprice attribute. In this case, we need to replace $\beta^c_{ip} d_p$ in Equation (12) with $\underline{\beta}^c_{ip}\underline{d}_p + \bar{\beta}^c_{ip}\bar{d}_p$, where

$$\underline{\beta}^c_{ip} = \beta_{ip}(\underline{p} - \tilde{p}), \qquad \bar{\beta}^c_{ip} = \tilde{\beta}_{ip}(\bar{p} - \tilde{p}), \tag{17}$$

$$\underline{d}_p = \begin{cases} 1 & \text{if } p = \underline{p} \\ 0 & \text{otherwise,} \end{cases} \qquad \bar{d}_p = \begin{cases} 1 & \text{if } p = \bar{p} \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

As a result, one can use conjoint analysis to estimate $\underline{\beta}^c_{ip}$ and $\bar{\beta}^c_{ip}$, and then substitute into Equation (13) the exchange rate specific to the price range of a product to compute a consumer's reservation price.

However, the economic theory of consumer choice does not treat price as any other attribute and it allows the price of a product to enter the utility function only through the budget constraint. This implies a linear price effect in the utility function. The key to reconciling the difference between theory and practice and to preserving the operational simplicity is to introduce some additional, reasonable assumptions to our theoretical derivations. In Appendix E, we show that if we assume p^y_i to be different in a high-price vs. a low-price environment, we could reasonably use Equation (17) to recover from conjoint estimations the exchange rate for a specific price range.

In summary, to estimate a consumer's reservation price for a product, we can simply conduct a regular conjoint analysis and use Equation (13) to compute the reservation price when each product attribute has only two levels of realization. When a nonprice attribute has three levels of realization, the two dummy variables assigned to the attribute in conjoint analysis should use the intermediate level as the default. When price also has three levels of realization, we simply assign two dummy variables, again with the intermediate level as the default. Once the conjoint parameters for the dummy variables are estimated, we can use Equation (17) to find the exchange rate appropriate to the price range of the product in question and use Equation (13) to compute reservation price.

4. Application

In this section, we present a pilot application to illustrate our approach. The primary purpose of this application is to show how our approach allows a researcher to estimate consumer reservation prices at the individual level with ease. By analyzing the estimated reservation prices, a researcher can then make product and pricing decisions with the same analytical flexibility and simplicity as afforded by traditional conjoint. However, we show that the strategy prescriptions for product introduction and pricing based on our approach differ significantly from those based on traditional conjoint, as our approach takes into account the market expansion effect and does not presume unconditional purchase by the target market.

To continue with the Compaq example discussed in the introduction, suppose that Compaq's management has decided that processing speed, hard drive, memory, price, and brand name are the five attributes

Table 1 Aggregate Conjoint Results[1]

Brand	Level	Coefficient	Standardized coefficient
Price	—[2]	−0.0225	−0.252
Brand	Dell	17.36	0.259
	Generic	0[3]	0
	Compaq	12.04	0.207
Memory	32 MB	−9.67	−0.144
	64 MB	0	0
	96 MB	4.67	0.070
Speed	266 mHz	0	0
	300 mHz	7.89	0.136
Hard drive	3 GB	0	0
	4 GB	2.42	0.041

[1]All coefficients are significant at α 0.01.

[2]We used three price levels \$1,999, \$2,599, and \$2,895. Using the Chow test, we failed to reject the null hypothesis that the price effect is linear ($p > 0.1$). We therefore report the results of the regression model with the linear price effect.

[3]0 indicates the base level for dummy coding.

that consumers value.[4] The levels of each of these attributes are given in Table 1 (Columns 1 and 2). To simplify the application further, assume that Dell is already selling a notebook computer with 266 mHz in speed, 64 MB in memory, and 4 GB in hard drive at \$2,599. We hereafter refer to this product as DELL. Compaq must decide whether to enter the market using a *penetration strategy*, introducing a low-end product (*CPQL*) with 266 mHz in speed, 32 MB in memory, and 3 GB in hard drive in the price range of ($\$1,999 \le p \le \$2,599$); or a *skimming strategy*, introducing a high-end product (*CPQH*) in a high price range ($\$2,599 \le p \le \$2,895$); or a *product line strategy*, introducing both *CPQL* and *CPQH* simultaneously in their respective price range.[5] The question is which strategy Compaq should pursue and at what price(s).

Conceptually, Compaq can answer this question by estimating the demand for *CPQL*, given that only *CPQL* and *DELL* are available in the market, the demand for *CPQH* when only *CPQH* and *DELL* are available, and the demand for both *CPQL* and *CPQH* when all three are available. It can then simulate the profit for the three different product introduction scenarios based on its own cost structure and choose the scenario and price that generate the most profit for the company. To add some realism to this application, we surveyed a random sample of MBA students in a major East Coast University to generate the demand information. For this survey, we used a 16-trial orthogonal design *à la* Addelman (1962) and asked each subject to rate each of these 16 notebook profiles on a 0 to 100 scale. The survey generated a total of 848 usable observations from 53 subjects. In addition, following Monroe (1990, p. 114), we asked each subject in three separate questions to indicate the acceptable price he or she would consider paying, respectively, for *CPQL*, *CPQH*, and *DELL*. We further asked each subject at the end of the survey to indicate whether or not she or he will purchase *CPQL* for \$1,999 if that is the only choice available in the market, and the same question is repeated for *CPQH* at \$2,895 and *DELL* at \$2,599.

In Table 1, we report the raw and standardized conjoint coefficients for the whole sample. All coefficients are statistically significant with the expected signs. The standardized coefficients suggest that brand and price are the most important attributes, followed by memory and speed. Hard drive plays a minor role in consumer preference for notebooks, probably because of the small GB range we tested.

4.1. A Tale of Two Models

Using the *individual-level* conjoint coefficients, we first conduct conventional market share simulations for different product introduction scenarios and price ranges. The results are summarized in Table 2 for each strategy scenario.

From Table 2, we can see that traditional conjoint simulations can generate several managerial insights. First, in terms of market shares, Dell is most vulnerable to Compaq's product introduction at the high end. At the \$2,599 price, Compaq can steal 69.6% from Dell if it enters at the high end but only 7.7% at the low end. However, by giving consumers more options to choose from, a product line strategy by Compaq can

[4] Our design of this application is adapted from Lehmann et al. (1997).

[5] Obviously, to narrow down to these three strategic options, many other factors such as market dynamics, consumer acceptance, brand positioning, etc., must be considered. However, using the procedure we describe here for all possible permutations of the product profiles can also help.

Table 2 Traditional Conjoint Market Share Simulation Results*

	Compaq pricing		Share		
Strategy	P_{CPQL}	P_{CPQH}	Q_{DELL}	Q_{CPQL}	Q_{CPQH}
Penetration	$1,999		51.7	48.3**	
(introduction at low end)	$2,599		92.3	7.7	
Skimming		$2,599	30.4		69.6
(introduction at high end)		$2,895	50.2		49.8
Product line	$1,999	$2,895	28.5	37.3	34.2
(introduction at both ends)	$1,999	$2,599	23.6	22.8	53.6
	$2,599	$2,895	46.9	5.1	48

*Simulations are conducted using the share of preference rule. The results are only slightly different when using the first choice rule. The quantity demanded is expressed as percentage of the target market. All numbers are rounded up. P_i and Q_i, where $i = DELL, CPQL, CPQH$, are price and sales for product profile i, respectively.

**To be read as follows: When Compaq enters with low-end notebook priced at $1,999, Dell's share is 51.7% and Compaq's share for *CPQL* is 48.3%

do significantly more damage to Dell than any single product strategy, rewarding it with up to 76.4% share. Second, the demand for the Compaq notebook is quite price elastic at the low end, with the arc price elasticity of demand $\epsilon = -5.6$, but much less so at the high end, with $\epsilon = -3.1$. Third, if Compaq introduces a product line and changes its prices from ($2,599; $2,895) to ($1,999; $2,895), i.e., lowering only the price for the low-end notebook, *CPQL* sales increase by about 32 percentage points in market share, about 18 percentage points coming from *DELL* (the customer switching effect) and about 14 points from *CPQH* (the cannibalization effect). If, on the other hand, Compaq changes its product line prices from ($1,999; $2,895) to ($1,999; $2,599), i.e., lowering only the price for the high-end notebook, *CPQH* will gain about 19 percentage points, with all but about 5 percentage points coming from *CPQL*. Overall, traditional conjoint simulations suggest an eager market that can perhaps be best exploited through a product line strategy.

The picture of the market changes quite substantially, however, if we examine the conjoint estimates through the lens of the approach we have proposed in this paper. We can apply Equation (13) to our individual-level conjoint estimates and then use Conditions (2)–(4) to assess the market demand for

Table 3 Demand Estimates Based on Consumer Reservation Price*

	Compaq pricing		Share			No
Strategy	P_{CPQL}	P_{CPQH}	Q_{DELL}	Q_{CPQL}	Q_{CPQH}	purchase
Penetration	$1,999		38.9	11.1		50.0**
(introduction at low end)	$2,599		46.3	1.9		51.9
Skimming		$2,599	18.5		33.3	48.1
(introduction at high end)		$2,895	24.1		27.8	48.1
Product line	$1,999	$2,895	22.2	5.6	24.1	48.1
(introduction at both ends)	$1,999	$2,599	18.5	1.9	31.5	48.1
	$2,599	$2,895	24.1	0	27.8	48.1

*The quantity demanded is expressed as percentage of the target market. All numbers are rounded up. P_i and Q_i, where $i = DELL, CPQL, CPQH$, are price and sales for product profile i, respectively.

**With Dell only in market, the nonpurchase rate is 53%. Thus, the introduction of *CPQL* has expanded the market by 3%.

different strategy scenarios while allowing for the market expansion effect. The results for each strategy scenario are summarized in Table 3. As a benchmark, our analysis shows that Dell's market penetration would be about 47% if its notebook is priced at $2,599 and is a monopoly. The untapped 53% of the market may decrease when Compaq enters the market, thus enabling us to gauge the market expansion effect.

From Table 3, we can see that a new product introduction at the low end has very limited market potential, capturing 11.1% of the target market at best. About eight percentage points of this demand come from Dell (Dell's share decreases from 47% in the benchmark case to 38.9% after Compaq enters with CPQL at $1,999). Three points result from market expansion (the category penetration increases from the benchmark case of 47% to the post-Compaq rate of 50%). Furthermore, the demand for *CPQL* is quite elastic, with the arc price elasticity $\epsilon = -5.42$. A price increase by Compaq from $1,999 to $2,599 for *CPQL* will reduce its share to a mere 2%. Thus, through the lens of the augmented approach, *CPQL* is drastically less attractive than what traditional conjoint suggests. This is because the traditional approach presumes full and unconditional market participation by all surveyed subjects and seriously inflates, in this application, the number of Compaq's customers. Once that presumption is dismissed, the augmented approach suggests a rather dismal prospect of profitability for Compaq at the low end of the market.

At the high end, the demand for *CPQH* is considerably less price sensitive with $\epsilon = -1.67$. At the high price of \$2,895, Compaq can capture 27.8% of the target market, with about 23 percentage points from *DELL* and about 5 points from market expansion. A price decrease from \$2,895 to \$2,599 for *CPQH* will draw approximately 5 more percentage points from *DELL* without expanding the market. Thus, relative to the entry at the low end, the augmented approach suggests that the *CPQH* introduction has an immensely larger market share for Compaq.

Compaq can enhance its high-end entry by simultaneously introducing the low-end product. However, this product line strategy brings little additional gain to Compaq, although consumers have one more option. From Table 3, we can see that Compaq's share of the target market with the product line strategy is not significantly different from what the company would capture with the high-end product alone. This suggests that the customers in this target market are mostly high-end purchasers, a characterization that fits rather well with the profiles of the MBAs we have surveyed. In fact, Table 1 shows that brand is slightly more important than price for these students.

Since two different approaches paint two different pictures about the market, it is not surprising that we may come to a different decision with regard to Compaq's product introduction strategy and pricing if we use this augmented conjoint approach rather than traditional conjoint. To see this, note that Tables 2 and 3 contain sufficient information for us to fit a linear demand curve for each product in each strategy scenario in the given price range. With additional costs information, we can easily determine the optimal price(s) and payoffs for a specific strategy scenario and then proceed to determine the most profitable strategy for Compaq to pursue. To carry through with this application, let us assume that the target market has one million consumers. The variable costs for the low-end notebook are \$1,400 and those for the high-end \$1,600. Furthermore, for simplicity we assume that the fixed cost associated with producing, marketing, and distributing the low-end notebook alone is \$300 million and that for the high-end notebook it is \$310 million. The fixed costs for the whole product line are \$330 million due to scale economies in marketing and distribution.

Under this cost structure, the traditional conjoint analysis suggests that Compaq should take the product line strategy, selling its high-end product for \$2,895 and its low-end product for \$2,324 to capitalize on the expected strong demands at both ends of the market. The estimated profit from the product line strategy are \$393 million. The skimming strategy, selling *CPQH* for \$2,619, is the second best, generating an estimated profit of \$385.6 million.

However, our augmented conjoint suggests a strikingly different product introduction and pricing strategy for Compaq. As the high-end product generates a strong customer switching effect and the maximum market expansion effect, the skimming strategy is the best entry strategy for Compaq: entering the high end of the market at the price point of \$2,895. The estimated profit from this strategy is \$50 million, which is significantly higher than the profit from the product line strategy (\$32.76 million). In this market, the product line strategy suffers from the fact that it generates little incremental sales while requiring additional development costs. It is interesting to note that traditional conjoint and our augmented approach make very different predictions about the maximum profits that Compaq can gain from the market. Traditional conjoint yields a high profit estimate in this application because it assumes full participation of all consumers in the target market.

This difference in strategy prescriptions means that Compaq would have to face a dire consequence if it makes the entry decision based on a wrong model. If, in fact, not every consumer in the target market will purchase unconditionally from one of the two brands and the market expansion effect is present, it would cost Compaq dearly if it were to pursue the wrong strategy of the product line, following the prescription from traditional conjoint, rather than the right strategy of skimming. The wrong choice of strategy in this case would mean a substantial amount of forgone profits for Compaq.

4.2. Prima Facie Validity

There are good reasons to believe that the augmented approach may produce a better strategic prescription in this application. From a theoretical perspective, the validity of traditional conjoint rests on the assumption that all the consumers in the target market make a purchase in a product category regardless of what product and pricing strategies the firms take or whether all competing products and brands in a market are included in a research design. However, this assumption is quite problematic in the context of this application, and indeed it is unlikely to hold for most practical applications. From an empirical perspective, we can establish some face validity here for our model by comparing the reservation prices and choices predicted by our model with the self-stated reservation prices and choices from the subjects we have surveyed. We will further examine the predictive validity using holdout samples in the next section.

Recall that we have asked our subjects to state their reservation prices for *CPQL*, *CPQH*, and *DELL*. Although biased, these self-stated reservation prices should have some positive correlation with their corresponding "true" reservation prices. Thus, if our model has any validity in capturing actual consumer reservation prices, we would expect the reservation prices predicted by our model to correlate

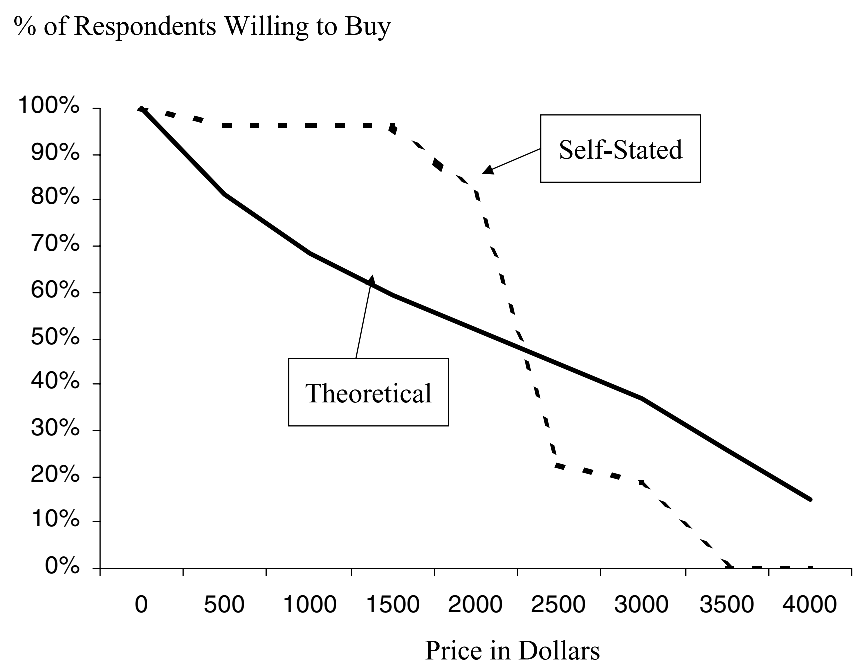
Table 4 Correlation Between Predicted and Self-Stated Reservation Prices (Augmented Conjoint)

Predicted reservation price for	Mean reservation price (90% Confidence interval)	Correlation: Self-stated reservation price for *DELL*	*CPQL*	*CPQH*
DELL	\$2,705 ($330–$5,164)	0.43**		
CPQL	\$1,926 ($0–$4,325)		0.15	
CPQH	\$3,141 ($330–$7,300)			0.28*

**Significant at $\alpha = 0.0017$ level; *Significant at $\alpha = 0.0478$ level.

with the *self-stated* reservation prices. In Table 4, we report the results of this correlational analysis. The mean self-stated reservation prices for products *DELL*, *CPQL*, and *CPQH* are, respectively, \$2,341, \$1,854, and \$2,643, and they are all lower than their corresponding predicted value (see Table 4). This outcome is rather expected, as subjects tend to understate their reservation prices (Monroe 1990, p. 107). This bias will, of course, exaggerate the demand at low prices and understate the demand at high prices, as we show in Figure 1 for *DELL*. However, what

Figure 1 Theoretical and Self-Stated Demands



is revealing is the fact that our estimated reservation prices are positively correlated with the self-stated reservation prices in all three product scenarios, with the correlations for *DELL* and *CPQH* both being statistically significant. The correlation for *CPQL* is statistically insignificant. Perhaps this is because most of our subjects are high-end buyers and they may have a higher degree of uncertainty about what they are willing to pay for a low-end product.

The augmented conjoint can be put to a more stringent test by examining the quality of choice predictions by the model. We make choice predictions by comparing a product's estimated reservation price with its actual price (see Equation (3)). We then compare the predicted choices with the subjects' revealed choices. We conduct this analysis for *DELL*, *CPQL*, and *CPQH*. The hit rate for *DELL* is 60.4%, which is statistically significant at $\alpha = 0.10$, and the hit rate for *CPQH* is 62.3%, which is significant at $\alpha = 0.05$. However, the hit rate for *CPQL* is only 54.7% and is not significant. We performed the same predictions using the self-stated reservation prices. The results show that our approach performed better for *CPQH* and *DELL*, but worse for *CPQL*. This result is generally consistent with the finding in Kalish and Nelson (1991).

Overall, our model performs reasonably well in capturing subjects' reservation prices and predicting their choices, which offer prima facie evidence in support of our theory-based augmentation of conjoint as a useful tool in aiding managerial decision making.

5. Assessing Predictive Validity Through Holdout Samples

To further assess the predictive validity of our approach and to compare its performance relative to models that capture the market expansion effect, we use a dataset from a commercial study of automobile batteries.[6] A multinational manufacturer of automobile batteries sponsored this study in an effort to improve its marketing and product design in the replacement market. The marketing research group in charge of the project selected six attributes after in-depth consumer interviews. They are brand (four brands: A, B, C, D), price (\$60, \$75, \$90), built-in charge meter (no, yes), environmental safety (no, yes), rapid recharge (no, yes), and battery life (standard, 50% longer). An orthogonal design of 32 profiles was used. Personal interviews were conducted at outlets where replacement car batteries were sold. Respondents were screened to be the key decision makers for car battery purchases. In exchange for a payment, each respondent evaluated 32 profiles descriptions. Each respondent first indicated if he or she would consider buying the described car battery and would then rate it on a 1–100 preference intensity scale only if the profile is considered (on average, 21.7% of the observations indicated no purchase). The order of profile presentations was randomized across respondents. In this study we use data from 169 respondents, totaling 5,408 observations (169 × 32 profiles) available to us. For validation purposes, we use 26 randomly drawn profiles for calibration and the remaining 6 profiles for holdout sample validation.

Unlike data typically collected in conjoint analysis studies, the car battery dataset is left-censored (i.e., preferences are observed only for products that are considered for purchase). As we show below, this left-censoring simplifies the estimation of reservation prices for product profiles. Recall that, by definition, consumer i will purchase product $\mathcal{P}$ if $r_i(\mathcal{P}) \geq p$. This means, from Equation (14), that the consumer will purchase the product if

$$\frac{\Delta p}{\beta_{ip}^c}\left(\sum_{k=1}^{N}\frac{\beta_{ik}^c}{\Delta A_k}A_k\right) - \frac{\Delta p}{\beta_{ip}^c}\left(\sum_{k=1}^{N}\frac{\beta_{ik}^c}{\Delta A_k}T_k\right) \geq p. \qquad (19)$$

Letting $\beta_{ip} = \beta_{ip}^c/\Delta p$ and with some simple algebraic manipulations, Condition (19) can be written as

$$\beta_{i0} + \left(\sum_{k=1}^{N}\frac{\beta_{ik}^c}{\Delta A_k}(A_k - \underline{A}_k)\right) - \beta_{ip}p \geq \beta_{i0} + \left(\sum_{k=1}^{N}\frac{\beta_{ik}^c}{\Delta A_k}(T_k - \underline{A}_k)\right). \qquad (20)$$

Note that the expression $(A_k - \underline{A}_k)/\Delta A$ in the second term of the left-hand side of Equation (20) takes

[6] To maintain confidentiality, we disguised the type of batteries being studied and the identity of some attributes.

on the value of either 1 or 0 when the realization of the attribute has two levels and can be simplified as d_k.[7] The right-hand side of Equation (20) is constant over product profiles and we denote it by $\bar{c}_i$. Then, Condition (20) can be simplified as

$$\beta_{i0} + \sum_{k=1}^{N} \beta_{ik}^{c} d_k - \beta_{ip} p \geq \bar{c}_i. \tag{21}$$

To estimate the parameters in Equation (21) from censored preference data, define a partially latent utility variable

$$U_i^*(\mathscr{P}) = \beta_{i0} + \sum_{k=1}^{N} \beta_{ik}^{c} d_k - \beta_{ip} p + \epsilon_i. \tag{22}$$

$U_i^*(\mathscr{P})$ is related to the observed (left-censored) conjoint preferences $U_i(\mathscr{P})$ as follows:

$$U_i(\mathscr{P}) = \begin{cases} U_i^*(\mathscr{P}) & \text{if } U_i^*(\mathscr{P}) \geq \bar{c}_i, \\ 0 & \text{if otherwise,} \end{cases} \tag{23}$$

where ϵ_i is an error term independently and identically distributed as $N(0, \sigma_i^2)$. Note that as β_{i0}^c and $\bar{c}_i$ are both constant for respondent i, only their difference is estimable.

Once the parameters $\beta_{i0}^c - \bar{c}_i$, all β_{ik}^cs, and β_{ip} are estimated, it is easy to show that the consumer reservation price for profile $\mathscr{P}$ is recovered as

$$r_i(\mathscr{P}) = \frac{\beta_{i0}^c - \bar{c}_i}{\beta_{ip}} + \frac{1}{\beta_{ip}} \sum_{k=1}^{N} \beta_{ik}^c d_k. \tag{24}$$

It is important to point out that using the Tobit model specification in Equations (22) and (23) to estimate the consumer reservation price has two practical advantages. First, as T_ks are all absorbed in $\bar{c}_i$ in Equation (24), one need not estimate T_ks directly in order to estimate a consumer's reservation price. Second, one no longer needs to find a proper default in specifying a nominal variable. Take brand names, for instance. If there are three brand names, say Brands A, B, and C, and one generic name, one needs to specify three brand dummies using the generic name as the default when we use traditional conjoint analysis (see §3). Then, these brand dummies enter into Equation (23) as $\beta_{iA} d_A + \beta_{iB} d_B + \beta_{iC} d_C$. However, in practice, it may be difficult to find a generic name from which a consumer derives zero attribute utility. Indeed, researchers typically code only two brand dummies, say, $\tilde{d}_B$ and $\tilde{d}_C$, using Brand A as the default. Fortunately, when using the Tobit model in Equation (23), a generic default is not necessary for estimating a consumer's reservation price.

To see this, note that given these two ways of specifying the dummy variables, we necessarily have $\beta_{iA} d_A + \beta_{iB} d_B + \beta_{iC} d_C \equiv \beta_{iA}(1 - \tilde{d}_B - \tilde{d}_B) + (\beta_{iB} + \beta_{iA})\tilde{d}_B + (\beta_{iC} + \beta_{iA})\tilde{d}_C$, which we can further simply as

$$\beta_{iA} d_A + \beta_{iB} d_B + \beta_{iC} d_C \equiv \beta_{iA} + \beta_{iB} \tilde{d}_B + \beta_{iC} \tilde{d}_C. \tag{25}$$

When the right-hand side of Equation (25) is used in Equation (23), β_{iA}, a constant, is absorbed into $\bar{c}_i$ and needs not be explicitly estimated to derive a consumer's reservation price. However, our derivation process shows that this advantage, along with the advantage of not estimating T_ks, comes at the cost of not being able to quantify specific attribute values. In other words, the gain in the ease of estimation comes at the expense of losing more detailed managerial insights.

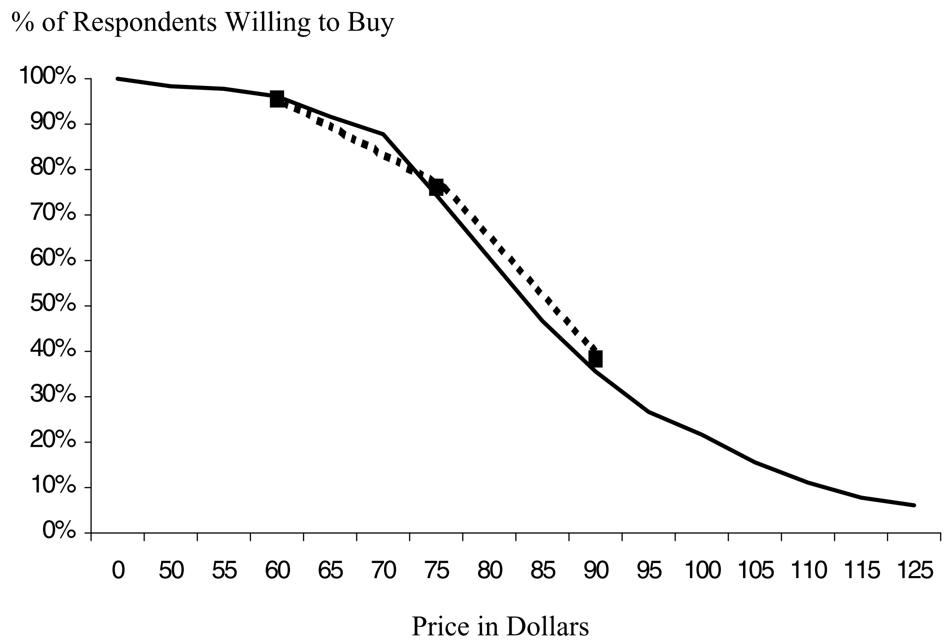
We analyze the car battery data using our reservation price model (see Equations (22) and (24)) and compare our results to those from the consideration set approach proposed by Jedidi et al. (1996) which captures the market expansion effect through a Tobit model formulation (see also Malhotra 1986). Because our interest is in estimating individual-level reservation prices, we estimate both models using PROC LIFEREG in SAS for each respondent.[8] To conserve space we only report summary statistics for model fit and predictive validity for both models. We also report the distribution of consumer reservation prices and present the demand curves produced from both models.[9]

[7] When the realization has three or more levels, we can similarly write two or more dummies following the steps in Appendices D and E.

[8] The main difference between the two models lies in the way price enters the utility function. The reservation price approach treats price linearly (see equation (22)) whereas the consideration set approach treats price via two dummy variables. Note that the estimation in Jedidi et al. (1996) is performed at the segment level.

[9] Further detailed results can be obtained from the authors.

Figure 2 Estimated Demand for a Brand D's Product*



* The solid line is based on our approach. The dotted line is based on Jedidi, Kohli, and Desarbo (1996).

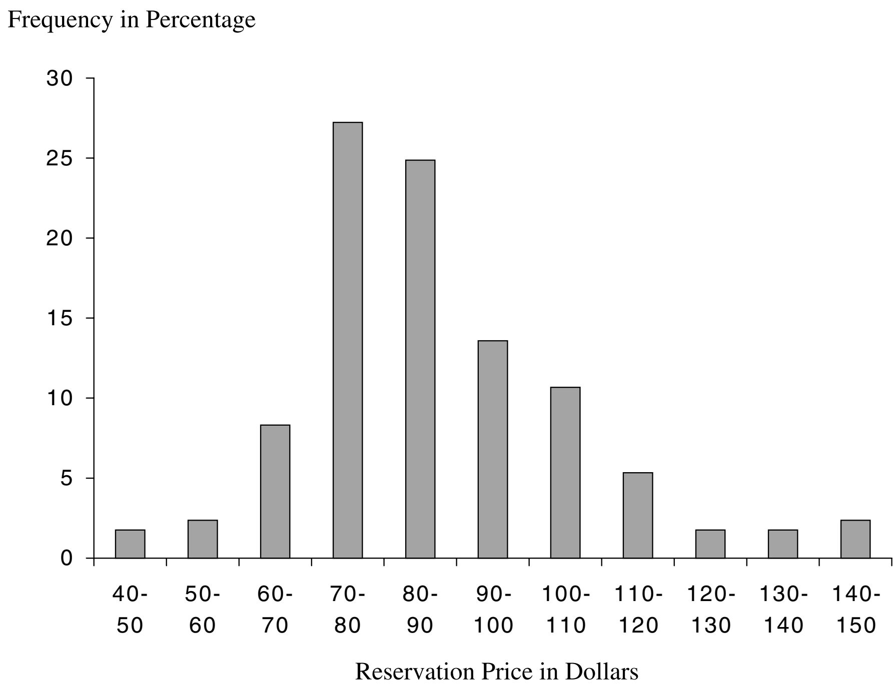
The goodness-of-fit statistics are excellent for both models. Using the same criteria as in Kalish and Nelson (1991), the average Spearman rank correlation between actual preference rankings and predicted surplus rankings is 0.834, and the average purchase incidence hit rate is 91.8% for our reservation price model. For the Jedidi et al. model, the average Spearman rank correlation between actual and predicted preference rankings is 0.85, while the average purchase incidence hit rate is 92.5%.

Figure 2 illustrates the differences between the demand curves obtained from our model and that of Jedidi et al (1996) for a Brand D battery with no built-in charge meter, no rapid recharge, no environmental safety, and standard battery life. This figure is constructed differently for each approach. For our approach, we first computed reservation prices for each respondent for the above product profile (see Figure 3). We then computed the percentage of respondents whose reservation price is greater than the actual price, which we varied from \$0 to \$125. For the Jedidi et al. approach we computed the percent of respondents whose utility exceeds the threshold for each price level (i.e., \$60, \$75, and \$90).

To assess and compare predictive validity, we used the parameters from each model to predict purchase incidence, preference ranking, and choice for six holdout profiles. Specifically, for our approach we computed the surplus (reservation price minus actual price) for each of these profiles. We predict purchase incidence if the surplus of the profile in question is positive. We predict choice of a profile if its surplus is the largest among the considered profiles. Similarly, for the Jedidi et al. approach, we predict purchase incidence if the utility of the profile is greater than the threshold and choice if its utility is maximum among the considered profiles. Using the same predictive validity statistics as in Kalish and Nelson (1991), the purchase incidence hit rate is 86.00% for our model and 86.25% for the Jedidi et al. model, whereas the choice hit rates are, respectively, 65.10% and 66.6%. For our model, the Spearman rank correlation between the actual preference rankings and the predicted surplus rankings is 0.836. For the Jedidi et al. model, the rank correlation between actual and predicted preferences is 0.834.

In sum, both approaches performed very well in predicting holdout profile preferences, and well

Figure 3 Distribution of Consumer Reservation Prices



beyond chance. Obviously, the Jedidi et al. approach performed slightly better than our approach. This is rather expected because the Tobit model upon which Jedidi et al. is based allows for possible nonlinear price effect through multiple price dummies in utility equation (see Footnote 8), whereas our theory-based approach only let price enter a utility function through the budget constraint and hence allows for only a linear price effect. However, the advantages of our approach are equally obvious in that it generates consumer reservation prices at the individual level (see Figure 3) and allows for nonlinear demand estimation (see Figure 2).

6. Conclusion

Our main contribution in this paper is to provide the proper transformation to estimate consumers' reservation prices from conjoint. We show how conjoint analysis can be integrated with the principles of economics to estimate consumers' reservation prices. This integration is possible fundamentally because a consumer's response to changes in price and other attributes for a product contains information about her money's worth, or her internal exchange rate between money and the utility of consuming the product. This exchange rate allows us to gauge a consumer's willingness to pay for a specific bundle of nonprice attributes. Thus, we can determine how much a consumer is willing to pay for a product and how much surplus a consumer will obtain from a product at a given price.

Knowledge of consumer reservation prices in a practical setting offers a much-needed decision aid for managers. Such knowledge takes their decision making from the choice arena to the value arena and offers them a fresh, direct perspective on the economics of their strategic alternatives. By using our approach, managers can assess the value of an attribute, the value of a product offering, and the value of a customer. This value perspective bridges theory and practice, and enables managers to implement many marketing strategies and pricing tactics that hitherto remain mostly theoretical curiosities.

Specifically, our pilot application shows that this value perspective allows managers to study consumer purchase decisions and estimate the full impact of their decisions on demand, whether they are making product or pricing decisions. By assessing in a single model all three demand effects, namely customer switching, cannibalization, and market expansion, managers can then decide with some rigor and confidence whether to use a skimming, penetration, or product line strategy when entering a market. Our pilot application shows that our approach can provide a distinct perspective on a market and can help managers to make better strategic decisions.

Our theoretical derivations also validate a common conjoint practice of converting attribute utility changes to dollar values (see Dolan and Simon 1996, pp. 58–59 for an example). For instance, suppose a price decrease, say, from \$2,599 to \$1,999, produces the same increase in utility as a change in processing speed from 266mHz to 300mHz. Then, we can conclude that the improvement in processing speed is worth \$600 for the consumer. With this and cost information, managers can decide whether it is more profitable to provide more processing speed or to reduce price. Our derivations confirm that this kind of analysis is theoretically sound. Equation (13) clearly assigns a dollar value to each nonprice attribute (exchange rate $\times$ attribute utility). Our derivations, however, clarify that it is inappropriate to multiply the exchange rate with the total utility from conjoint to estimate the consumer reservation price. The correct transformation must exclude the intercept and the price effect from total utility while properly scaling the attribute utilities.

It is important to emphasize that our approach provides a unique analytical apparatus that can estimate both consumer reservation prices and assess all three demand effects. It is also important to emphasize that our approach has two distinct advantages. First, our model is based on the standard economic theory of consumer choice, yet it retains the conceptual and operational simplicity of traditional conjoint. It entails no new data gathering or estimation techniques and imposes no expedient assumptions or any ad hoc rules to pin down consumer buy or no-buy decision. Any practitioner or student who knows how to use conjoint can easily use this augmented approach, all within the framework of utility theory. Thus, this approach serves not only practical functions, but also pedagogical purposes. Second, the augmented conjoint estimates *individual-level* reservation prices for a specific product. Thus, it can potentially aid the implementation of one-to-one pricing.

In addition, we demonstrate, using commercial data, that our approach can be easily implemented through a Tobit model specification with a linear price effect. Although this specific way of implementing our approach has a more stringent data requirement, it offers the advantage of bypassing some conjoint design and estimation issues and is advisable when researchers care only about reservation prices but not attribute values. Our application to the automobile battery data shows that our approach has good predictive validity both by itself and relative to the utility-based approach proposed by Jedidi et al. (1996).

However, as our approach is dependent on traditional conjoint, it inherits all its shortcomings. Thus, the usual cautions associated with applying conjoint and making inferences from the analysis must be exercised in applying this approach. Specifically, it is worth noting that our model cannot capture any purchase dynamics or accommodate multiple-unit purchases. Furthermore, our model also relies on (piecewise) linear extrapolations and the additive nature of attribute utilities. Such linear approximations may not be accurate enough for some applications. Indeed, our model is not a statistical model and we do not quantify statistical errors inherent in our estimation of consumer reservation prices. Future research can extend our approach in that direction, perhaps following the approach proposed by Kohli and Mahajan (1991) or through a Bayesian approach. As the real test ground is in practical applications, this shortcoming can be minimized if every effort is made to validate and benchmark the results from the analysis. Like any other approach in marketing, the augmented conjoint can only aid, but not substitute for, sound managerial intuition and judgment.

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Appendix A. Existence of Consumer Reservation Price

We show that $r_i(\mathcal{P})$ as defined in Equation (1) always exists. To do so, we maintain the standard assumption that a consumer marginal utility from both "goods" is positive. Furthermore, we assume that it is never optimal for any consumer to purchase the product in question if the price for the product is as high as the consumer's income, or $U_i(\mathcal{P}, 0) < U_i(0, m_i/p_i^y)$. Define a consumer's utility gain function as

$$\mathcal{F}_i(p) = U_i\left(\mathcal{P}, \frac{m_i - p}{p_i^y}\right) - U_i\left(0, \frac{m_i}{p_i^y}\right). \tag{A.1}$$

Note that our two assumptions about a consumer's utility function imply $\mathcal{F}_i(0) > 0$ and $\mathcal{F}_i(m_i) < 0$. Since $\partial\mathcal{F}_i(p)/\partial p < 0$, there must always exist a $r_i(\mathcal{P}) \in (0, m_i)$ such that

$$\mathcal{F}_i(r_i(\mathcal{P})) = U_i\left(\mathcal{P}, \frac{m_i - r_i(\mathcal{P})}{p_i^y}\right) - U_i\left(0, \frac{m_i}{p_i^y}\right) \equiv 0. \tag{A.2}$$

Clearly, for any $p \le r_i(\mathcal{P})$, we must have $\mathcal{F}_i(p) \ge 0$ so that the consumer is better off purchasing the product. Otherwise, the consumer will not purchase the product as $\mathcal{F}_i(p) < 0$. Q.E.D

Appendix B. Equivalence between Utility Maximization and Surplus Maximization

We show that when a consumer's utility function is of the quasi-linear form, or $U_i(\mathcal{P}, y_i) = u_i(\mathcal{P}) + \alpha y_i$, where $\alpha > 0$, the consumer will choose Product A over Product B, given p_A and p_B, if and only if $s_A = [r_i(A) - p_A] \ge [r_i(B) - p_B] = s_B$.

For a consumer with income m_i and the price of consumption basket p_i^y, her utility from purchasing Product A at the price of p_A and that from purchasing Product B at p_B are respectively given by

$$U_i(A, p_A) = u_i(A) + \alpha\frac{m_i - p_A}{p_i^y}, \tag{B.1}$$

$$U_i(B, p_B) = u_i(B) + \alpha\frac{m_i - p_B}{p_i^y}. \tag{B.2}$$

Define $F(p_A, p_B) = U_i(A, p_A) - U_i(B, p_B)$. Then, consumer i will choose Product A over Product B if $F(p_A, p_B) \ge 0$ and choose Product B if otherwise. However, by definition, we have

$$\begin{aligned} F(p_A, p_B) &= \left\{u_i(A) + \alpha\frac{m_i - r_i(A) + s_i(A)}{p_i^y}\right\} \\ &\quad - \left\{u_i(B) + \alpha\frac{m_i - r_i(B) + s_i(B)}{p_i^y}\right\} \\ &= \left\{u_i(A) + \alpha\frac{m_i - r_i(A)}{p_i^y} - u_i(B) - \alpha\frac{m_i - r_i(B)}{p_i^y}\right\} \\ &\quad + \alpha\frac{s_i(A) - s_i(B)}{p_i^y}. \end{aligned} \tag{B.3}$$

Note that the first term in Equation (B.3) is, by the definitions of $r_i(A)$ and $r_i(B)$ in Equation (1), zero. Thus, we have

$$F(p_A, p_B) = \frac{\alpha}{p_i^y}\{s_i(A) - s_i(B)\}. \tag{B.4}$$

This implies that we have $F(p_A, p_B) \ge 0$ if and only if $s_i(A) \ge s_i(B)$. Q.E.D

Appendix C. Three Levels of Realization

Suppose that the kth attribute has three levels of realization. As a continuous variable in the attribute space, we have $A_k \in [\underline{A}_k, \overline{A}_k]$. Since the level of this attribute can take on three values, it is desirable in our utility specification to account for possible diminishing or increasing utility from this attribute as the level of the attribute increases. This can be accomplished by specifying $u_{ik}(\mathcal{P})$ in Equation (6) not as proportional to, but as piecewise linear in, attribute k. Let $\widetilde{A}_k$ be an intermediate point in the range for A_k, or $\underline{A}_k < \widetilde{A}_k < \overline{A}_k$. In practice, we can take $\widetilde{A}_k$ as the intermediate level of realization for attribute k. We can specify

$$u_{ik}(\mathcal{P}) = \begin{cases} \underline{\beta}_{ik} A_k & \text{if } A_k \in [\underline{A}_k, \widetilde{A}_k] \\ \underline{\beta}_{ik}\widetilde{A}_k + \bar{\beta}_{ik}(A_k - \widetilde{A}_k) & \text{if } A_k \in (\widetilde{A}_k, \overline{A}_k]. \end{cases} \tag{C.1}$$

Equation (C.1) is illustrated in Figure 4. If $\underline{\beta}_{ik} = \bar{\beta}_{ik}$, we have a linear specification as in Equation (6). However, if $\underline{\beta}_{ik} > \bar{\beta}_{ik}$ ($\underline{\beta}_{ik} < \bar{\beta}_{ik}$), the consumer derives diminishing (increasing) utility from the attribute.

To facilitate our derivation, we define the following two switching functions:

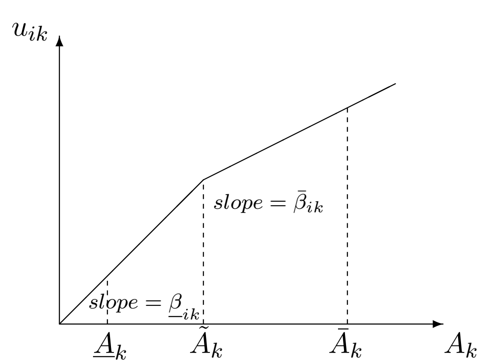
$$\delta_1(A_k) = \begin{cases} 1 & \text{if } A_k \in [\underline{A}_k, \widetilde{A}_k], \\ 0 & \text{if otherwise;} \end{cases}$$

$$\delta_2(A_k) = \begin{cases} 1 & \text{if } A_k \in (\widetilde{A}_k, \overline{A}_k], \\ 0 & \text{if otherwise.} \end{cases} \tag{C.2}$$

By these two definitions, for all $A_k \in [\underline{A}_k, \overline{A}_k]$, we have $\delta_1(A_k) + \delta_2(A_k) \equiv 1$. Then, Equation (C.1) can be written compactly as

$$u_{ik}(\mathcal{P}) = \delta_1(A_k)\underline{\beta}_{ik}A_k + \delta_2(A_k)\{\underline{\beta}_{ik}\widetilde{A}_k + \bar{\beta}_{ik}(A_k - \widetilde{A}_k)\}. \tag{C.3}$$

Figure 4 **Piece-Wise Linear Attribute Utility**



Since $\widetilde{A}_k - \underline{A}_k \neq 0$ and $\overline{A}_k - \widetilde{A}_k \neq 0$, with some simple algebraic manipulations and using $\delta_1(A_k) + \delta_2(A_k) \equiv 1$, we can write Equation (C.3) as

$$u_{ik}(\mathscr{P}) = -\underline{\beta}_{ik}(\widetilde{A}_k - \underline{A}_k)\frac{(\widetilde{A}_k - A_k)\delta_1(A_k)}{(\widetilde{A}_k - \underline{A}_k)} + \bar{\beta}_{ik}(\overline{A}_k - \widetilde{A}_k)\frac{(A_k - \widetilde{A}_k)\delta_2(A_k)}{(\overline{A}_k - \widetilde{A}_k)} + \underline{\beta}_{ik}\widetilde{A}_k, \tag{C.4}$$

for all $A_k \in [\underline{A}_k, \overline{A}_k]$.

To simplify notation, we define the following two dummy variables:

$$\underline{d}_k = \begin{cases} 1 & \text{if } A_k = \underline{A}_k, \\ 0 & \text{otherwise;} \end{cases}$$

$$\bar{d}_k = \begin{cases} 1 & \text{if } A_k = \overline{A}_k, \\ 0 & \text{otherwise.} \end{cases} \tag{C.5}$$

We also let

$$\underline{\beta}^c_{ik} = -\underline{\beta}_{ik}(\widetilde{A}_k - \underline{A}_k) \quad \text{and} \quad \bar{\beta}^c_{ik} = \bar{\beta}_{ik}(\overline{A}_k - \widetilde{A}_k). \tag{C.6}$$

Then, when A_k has only three levels of realization, i.e., $A_k = \underline{A}_k$, $\widetilde{A}_k$, or $\overline{A}_k$, it is straightforward to verify that for all A_k we have,

$$\underline{d}_k = \frac{(\widetilde{A}_k - A_k)\delta_1(A_k)}{(\widetilde{A}_k - \underline{A}_k)} \quad \text{and} \quad \bar{d}_k = \frac{(A_k - \widetilde{A}_k)\delta_2(A_k)}{(\overline{A}_k - \widetilde{A}_k)}. \tag{C.7}$$

Thus, Equation (C.4) can be simplified as

$$u_{ik}(\mathscr{P}) = \underline{\beta}^c_{ik}\underline{d}_k + \bar{\beta}^c_{ik}\bar{d}_k + \underline{\beta}_{ik}\widetilde{A}_k. \tag{C.8}$$

It is obvious from Equation (C.8) that an attribute with three levels of realization lends itself very well to conjoint estimation. All we need to do is to redefine $U_i(\mathbf{P}^l)$ as consumer i's utility from the product profile that has the lowest level of each two-level attribute and the intermediate level of each three-level attribute. Thus, we can simply substitute in the first two terms of Equation (C.8) for any attribute that has three levels of realization in Equation (12), as the last term in Equation (15) is canceled out when we take the difference between $U_i(\mathscr{P})$ and $U_i(\mathbf{P}^l)$. Once $\underline{\beta}^c_{ik}$ and $\bar{\beta}^c_{ik}$ are estimated through conjoint analysis, we can use Equation (C.6) to find $\underline{\beta}_{ik}$ and $\bar{\beta}_{ik}$. Then, Equation (C.1) will give us the estimate of $u_{ik}(\mathscr{P})$ that we need to calculate the consumer's reservation price using Equation (13).

Appendix D. Four or More Levels of Realization

We will focus on four levels of realization in our derivation. However, the same procedure can be applied to any higher levels of realization. For simplicity of notation, we omit the index number for the attribute and the consumer. Let A^i be the i's realization of a certain attribute, where $i = 1, 2, 3, 4$ and a larger i indicates a higher level of the attribute. To allow for diminishing utility, we can write the utility from the attribute as a piecewise linear function below:

$$u(\mathscr{P}) = \begin{cases} \beta_1 A & \text{if } A \in [A^1, A^2] \\ \beta_1 A^2 + \beta^2(A - A^2) & \text{if } A \in (A^2, A^3] \\ \beta_1 A^2 + \beta^2(A^3 - A^2) + \beta^3(A - A^3) & \text{if } A \in (A^3, A^4]. \end{cases} \tag{D.1}$$

As in Appendix C, we define the following three switching functions:

$$\delta_3(A) = \begin{cases} 1 & \text{if } A \in [A^1, A^2], \\ 0 & \text{otherwise;} \end{cases}$$

$$\delta_4(A) = \begin{cases} 1 & \text{if } A \in (A^2, A^3], \\ 0 & \text{otherwise;} \end{cases}$$

$$\delta_5(A) = \begin{cases} 1 & \text{if } A \in (A^3, A^4], \\ 0 & \text{otherwise.} \end{cases}$$

By these three definitions, for all $A \in [A^1, A^4]$, we have

$$\delta_3(A) + \delta_4(A) + \delta_5(A) \equiv 1. \tag{D.2}$$

We can then write Equation (D.1) as

$$u(\mathscr{P}) = \delta_3(A)\beta_1 A + \delta_4(A)\{\beta_1 A^2 + \beta^2(A - A^2)\} + \delta_5(A)\{\beta_1 A^2 + \beta^2(A^3 - A^2) + \beta^3(A - A^3)\}.$$

With some simple algebraic manipulations and using the Identity (D.2), we can write the above equation as

$$\begin{aligned} u(\mathscr{P}) = {} & \delta_3(A)\beta_1(A - A^1) + \delta_4(A)\beta_2(A - A^1) \\ & + \delta_5(A)\beta_3(A - A^1) + \beta_1 A^1 + \delta_4(\beta_1 - \beta_2)(A^2 - A^1) \\ & + \delta_5\{(\beta_1 - \beta_2)(A^2 - A^1) + (\beta_2 - \beta_3)(A^3 - A^1)\}. \end{aligned} \tag{D.3}$$

Note that the second line in Equation (D.3) is approximately zero if $\beta_1 \approx \beta_2$ and $\beta_2 \approx \beta_3$, which we will assume. Then, we have

$$\begin{aligned} u(\mathscr{P}) \approx {} & \delta_3(A)\beta_1(A - A^1) + \delta_4(A)\beta_2(A - A^1) \\ * \quad & + \delta_5(A)\beta_3(A - A^1) + \beta_1 A^1 \\ = {} & \delta_3(A)\beta_1(A^2 - A^1)\frac{(A - A^1)}{(A^2 - A^1)} + \delta_4(A)\beta_2(A^3 - A^1)\frac{(A - A^1)}{(A^3 - A^1)} \\ & + \delta_5(A)\beta_3(A^4 - A^1)\frac{(A - A^1)}{(A^4 - A^1)} + \beta_1 A^1. \end{aligned} \tag{D.4}$$

To simplify our notation, let

$$d_i = \delta_{i+2}(A)\left(\frac{A - A^1}{A^{i+1} - A^1}\right),$$
$$\beta^c_i = \beta_i(A^{i+1} - A^1),$$

where $i = 1, 2, 3$. Then, we have from Equation (D.4)

$$u(\mathscr{P}) \approx \beta^c_1 d_1 + \beta^c_2 d_2 + \beta^c_3 d_3 + \beta_1 A^1. \tag{D.5}$$

It is straightforward to show that d_i is simply a dummy variable indicating the $(i+1)$th level of realization with the lowest level of realization as the default. The last term will drop as we take the difference the way we do in the text for two levels of realization. Q.E.D

Appendix E. Price Dependent Exchange Rate

To introduce price-dependent exchange rate in the context of our model, we need to assume that p_i^y is different in a high-price vs a low-price environment. Then we can write a consumer's utility function as

$$U_i(\mathcal{P}) = u_i(\mathcal{P}) + \delta_1(p)\left\{\frac{m_i}{p_i^y} - \frac{p}{p_i^y}\right\} + \delta_2(p)\left\{\frac{m_i}{\tilde{p}_i^y} - \frac{p}{\tilde{p}_i^y}\right\}, \tag{E.1}$$

where $\delta_1(p)$ and $\delta_2(p)$ are as defined in Equation (16). With this specification, we have

$$U_i(\mathbf{P}^l) = u_i(\mathbf{P}^l) + \frac{m_i}{p_i^y} - \frac{\tilde{p}}{p_i^y}. \tag{E.2}$$

Taking the difference between Equations (E.1) and (E.2), we have

$$\begin{aligned} U_i(\mathcal{P}) - U_i(\mathbf{P}^l) &= \{u_i(\mathcal{P}) - u_i(\mathbf{P}^l)\} + \delta_1(p)\left\{\frac{m_i}{p_i^y} - \frac{p}{p_i^y}\right\} \\ &\quad + \delta_2(p)\left\{\frac{m_i}{\tilde{p}_i^y} - \frac{p}{\tilde{p}_i^y}\right\} - \frac{m_i}{p_i^y} + \frac{\tilde{p}}{p_i^y}. \end{aligned} \tag{E.3}$$

Let $\beta_{i0} = m_i/p_i^y$, $\beta_{ip} = 1/p_i^y$, $\tilde{\beta}_{i0} = m_i/\tilde{p}_i^y$, and $\tilde{\beta}_{ip} = 1/\tilde{p}_i^y$. We can write (E.3) as

$$\begin{aligned} U_i(\mathcal{P}) - U_i(\mathbf{P}^l) &= \{u_i(\mathcal{P}) - u_i(\mathbf{P}^l)\} + \{\delta_1(p)\beta_{i0} + \delta_2(p)\tilde{\beta}_{i0} - \beta_{i0}\} \\ &\quad - \{\delta_1(p)\beta_{ip} + \delta_2(p)\tilde{\beta}_{ip} - \beta_{ip}\}\tilde{p} - \delta_1(p)\beta_{ip}(p - \tilde{p}) \\ &\quad - \delta_2(p)\tilde{\beta}_{ip}(p - \tilde{p}) \end{aligned} \tag{E.4}$$

Note that if the difference between p_i^y and $\tilde{p}_i^y$ is small, which we can reasonably assume, we must have $\beta_{i0} \approx \tilde{\beta}_{i0}$ and $\beta_{ip} \approx \tilde{\beta}_{ip}$. Then, since $\delta_1 + \delta_2$, we must also have

$$\delta_1(p)\beta_{i0} + \delta_2(p)\tilde{\beta}_{i0} - \beta_{i0} \approx 0 \quad \text{and} \quad \delta_1(p)\beta_{ip} + \delta_2(p)\tilde{\beta}_{ip} - \beta_{ip} \approx 0. \tag{E.5}$$

Thus, from Equations (E.4) and (E.5), we must have

$$\begin{aligned} &U_i(\mathcal{P}) - U_i(\mathbf{P}^l) \\ &\quad \approx \{u_i(\mathcal{P}) - u_i(\mathbf{P}^l)\} - \delta_1(p)\beta_{ip}(p - \tilde{p}) - \delta_2(p)\tilde{\beta}_{ip}(p - \tilde{p}). \end{aligned} \tag{E.6}$$

The process of transforming Equation (E.6) into conjoint analysis specification is the same as in the text. Q.E.D

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