A HIERARCHICAL MODEL TO STUDY PRIMARY DEMAND

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of the Ohio State University

By

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*****

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To my parents Jai and Bhim Sain Arora,
my future wife Leigh Casares and my sister Neeru Setia.
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CHAPTER I

Introduction

Choice based models are widely used in marketing in order to relate consumer behavior to the marketing mix elements. For example, models utilizing consumer purchase data collected through scanner panels are used to understand the relationship between sales promotion and consumer choice. Similarly, models utilizing consumer preference data obtained through a technique such as conjoint analysis are used to relate product design features to choice.

From the perspective of a brand manager with the objective of increasing brand sales, it is important to develop an understanding of three consumer related questions. First, what are the factors which drive a consumer to purchase or not purchase from a given product category. Second, for a consumer who does purchase from the given product category what is the relationship between product characteristics of the available alternatives and purchase quantity. And third, what are the trade-offs that the given consumer makes between product attributes in order to make a choice decision.

Typical choice models (McFadden 1973, Guadagni and Little 1983) condition on the purchase event and focus on the effect of differences in the available alternatives on consumer choice. Other aspects of the purchase decision such as purchase/non-purchase
and purchase quantity are usually not considered. Although an analysis which is conditional on the purchase event is informative about trade-offs that a consumer makes between the available alternatives, it is not informative about why the consumer chooses to buy or not buy from a product category. Also, it does not provide any insights into the relationship between the attributes of the available alternatives and purchase quantity.

Information about purchase/non-purchase can potentially help develop an understanding of the factors which explain why some individuals do not buy from a given product category. An understanding of those factors can then be used to develop a marketing strategy which takes into consideration the possibility of converting current non-buyers into buyers in the product category of interest. Similarly, information about purchase quantity can be used to understand the relationship between product attributes and purchase quantity. An understanding of this relationship can be used to explore product design changes leading to increases in units sold to an individual consumer.

Unlike the analysis based upon conditional-on-purchase choice models which focuses on increase in market share, an analysis based upon information on purchase quantity focuses on increase in market size. A brand manager is likely to be interested in both these analyses because they allow her to adopt a marketing mix strategy which enhances a brand’s market share as well the market size. Such a marketing strategy would focus on increasing primary demand of a product, in addition to increasing the brand’s market share.

In this research I utilize both the purchase quantity and brand choice data to build a model to understand factors which influence primary demand. I use the economic
framework of utility maximizing consumer and build upon earlier work on discrete / continuous models of consumer demand (Hanemann 1984). The basic idea builds upon the microeconomic framework of consumer utility maximization subject to a budget constraint. Given this framework, it is reasonable to assume that a consumer is in or out of the market depending upon whether the utility per dollar of at least one available choice alternative is above some threshold level. Chiang (1991) and Chintagunta (1993) were the first to introduce the notion of such a threshold level. In this dissertation, this threshold level is referred to as the reservation value for the product. The reservation value is expected to be different across consumers. The data about purchase/non-purchase is informative about individual specific reservation value. For example, one can say that if it is observed that a consumer purchases an item from a given product category on a given purchase occasion then it must be that the chosen item offered a utility per dollar which was above her reservation value.

The proposed approach provides a measure of individual level reservation value which allows for an investigation of reasons for why some individuals buy or do not buy from a given product category. Through the distribution of heterogeneity of this threshold level measure, one can easily identify individuals with the highest probability of being converted from non-buyers to buyers.

I also relate product attributes to quantity purchased by a consumer. A measure of expenditure sensitivity to the utility per dollar of a product is obtained. This measure establishes a link between product design and quantity purchased at the individual level.
Heterogeneity in this measure across the population helps in identifying consumers with the largest potential to increase their expenditure in the product category of interest.

I study the issue of primary demand through a field study in which potential consumers of a food item are asked to indicate their product choice from a set of available alternatives and the likely purchase quantity for the chosen alternative. The proposed framework makes methodological as well as substantive contribution to the marketing literature.

The first methodological contribution of the dissertation is that it provides individual level estimates of reservation value and expenditure sensitivity parameters. The reservation value relates product design to the purchase/non-purchase decision of an individual and the expenditure sensitivity parameter relates product design to the purchase quantity of an individual. Chiang (1991) and Chintagunta (1993) also exploit the notion of reservation value (or price) but their approaches do not provide individual level estimates. A hierarchical Bayes model is used to estimate the proposed model at the individual level. Recent advancements in simulation based methods (Gelfand and Smith 1990) are used to overcome the computational difficulties associated with estimating hierarchical Bayes models. A unique advantage of the Bayesian formulation is that it provides empirical posterior distributions of individual level reservation value and expenditure sensitivity. Statistical properties of these individual level estimates can be easily studied from the posterior distributions. It is the inference at the individual level which allows me to investigate issues related to primary demand.
The second methodological contribution is to establish a link between conjoint methodology and the consumer decision of how much to buy. Traditionally, the use of conjoint analysis has been restricted to understanding the consumer choice decision only. By combining microeconomic theories with conjoint analysis, this dissertation studies consumer decisions of what to buy and how much to buy in a single unifying framework. The value of such a framework is that it provides additional information regarding marketing decisions. For example, the traditional conjoint analysis is useful in identifying individuals who are most likely to buy a given product design. The proposed framework, in addition to identifying the most likely buyers, also helps in identifying individuals who are most likely to buy large quantities of a given product design.

The substantive contribution of the dissertation is that it provides a formal framework to understand the link between product design and primary demand. From a brand manager's perspective, the framework assists in developing a product design strategy which increases total brand sales by increasing market share as well as the market size. Analysis at the individual level helps in identifying those consumers who have the largest potential to increase primary demand. A demographic, attitudinal or behavioral profile of these consumers can be used for targeting purposes. The framework is therefore useful for product introduction and/or product repositioning decisions.

From the above discussion, it is evident that issues relating to primary demand are relevant to a brand manager. However, Blattberg and Neslin (1989) note that there has been very little research done in this area. Most of what has been done has attempted to provide empirical evidence of the effect of promotion on primary demand (e.g. Ward and
Davis 1978). Data for this stream of research has often been obtained through natural experiments such as a ban on cigarette advertising (Holak and Reddy 1986) and a sudden increase in the price of pre-sweetened cereals caused by a sugar shortage (Neslin and Shoemaker 1983). Large variation in variables such as price and advertising are used to estimate consumer sensitivities to marketing mix elements at the aggregate level. Based upon the methodological and substantive contribution listed above, this dissertation offers a significant improvement over the current state of knowledge on the topic of primary demand as the existing research is limited to aggregate level empirical investigation of the effect of advertising and price on primary demand.
CHAPTER II

Literature Review

This chapter is divided into four parts. Part 1 deals with empirical studies attempting to demonstrate the relationship between marketing mix elements and primary demand. Part 2 provides a discussion on how conjoint analysis relates to the study of primary demand. Part 3 provides an overview of a class of models called the discrete/continuous models. These models are directly related to this research and are therefore discussed in some detail. The chapter ends with part 4 in which the contributions of this research to the marketing literature are discussed.

1. Empirical studies

Most literature on the issues related to primary demand is limited to attempts to demonstrate the link between marketing mix elements and primary demand. In this literature, analysis is carried out at the group level and no inference at the individual level is possible. Since these studies on primary demand have been conducted at the aggregate level, their purpose sometimes has been to study policy issues such as advertising controls and tax increases (Duffy 1989). Very little work has been done in studying primary demand from a brand manager's perspective. All of what has been done relates to exploring the link between marketing mix elements and purchase quantity (e.g. Neslin
and Shoemaker 1983). There has been no systematic investigation of the link between marketing mix elements and consumer purchase/non-purchase decision.

Empirical studies on primary demand related issues have relied upon either years of time series data or data obtained through a natural experiment. A natural experiment is characterized by large shifts in marketing mix variables for the entire industry and is caused by sudden changes in the operating environment of the industry. Examples include a government imposed advertising ban on the cigarette industry or a sugar shortage for the pre-sweetened cereals. The advantage of such natural experiments is that the variability in an independent variable such as price allows for an estimation of price elasticity which may not have been otherwise feasible because of a stable price level. The disadvantage is that large shifts in marketing variables are typically confounded with other industry specific changes. Next I outline some of the studies related to primary demand. I begin with studies which were based upon natural experiments. This will be followed by studies which relied upon time series data for an industry.

Neslin and Shoemaker (1983) use data from a natural experiment to estimate price elasticity of cereals. In 1974, the sugar shortage caused prices of pre-sweetened cereals to go up by 24% in nine months. By using data between 1973 and 1976 for the cereal industry, the authors concluded that the price elasticity of the pre-sweetened cereals is larger in magnitude than the cereal market as a whole. Based upon an aggregate analysis, it is noted that consumers substitute within the product category by switching to granola and low-sugar cereals when the price of pre-sweetened cereals goes up. Based upon this observation, it is concluded that a manufacturer should maintain a balanced product
portfolio containing low-sugar and granola brands, as well as pre-sweetened brands.

The Public Health Cigarette Smoking Act of 1970 banned all advertising of cigarettes on radio and television in the U.S. Holak and Reddy(1986) used industry and brand level data from this natural experiment for the pre-ad and post-ad ban eras to study issues related to price and advertising sensitivity and brand loyalty. The authors found that the post-ad ban era was characterized by a higher price sensitivity, lower advertising sensitivity and higher brand loyalty. Based upon these results, the authors list several managerial recommendations to cope with regulatory bans.

Selvenathan (1989) studied the impact of industry level advertising on industry level demand of beer. Based upon sales data for beer, wine and spirits between 1955 and 1975 in the United Kingdom, he found that beer advertising increased the demand of beer and decreased the demand of wines and spirits. Duffy (1985) also conducted a similar analysis for the alcoholic beverage industry in the United Kingdom and concluded that demand for beer, wine and spirits is predominantly influenced by income and price. Although industry advertising also affects primary demand, its effect is smaller. The author concludes that the large increase in consumption of alcoholic beverages in the United Kingdom between the period of 1963 and 1983 can not be attributed to advertising.

Waterson(1989) also studies the effect of advertising on alcohol consumption and concludes that based upon the empirical evidence this effect is insignificant. Leeflang and Reuiji(1985) conduct an empirical investigation of cigarette advertising on primary
demand for the German cigarette industry. The authors conclude that there is a positive influence of advertising on cigarette demand and that this influence goes down over time.

Three observations can be made from the empirical studies outlined above. First, from a managerial standpoint, the existing research does not provide a formal framework which assists in making decisions related to primary demand shifts. Second, existing research does not attempt to relate product design changes to primary demand and is restricted to studying the effects of advertising and price. A problem common across all the studies reported is that only one marketing variable is changing. Therefore the data is uninformative about the effect of product attributes on primary demand. And third, analysis is carried out at the group level and no inference at the individual level can be drawn.

The purpose of this dissertation is to develop a formal framework to study issues relating to primary demand. The proposed approach establishes the link between product design and primary demand. The analysis is carried out at the individual level to systematically explore differences among individuals with regard to the potential to increase primary demand. I adopt a conjoint analysis based approach to develop a formal framework to study primary demand from a brand manager's perspective. Next the relevant literature on conjoint analysis is discussed.

2. Conjoint Analysis

Conjoint analysis is widely used to help identify profitable product designs (Green and Krieger 1989, Kohli and Sukumar 1989, Dobson and Kalish 1992). The partworth estimates obtained from a conjoint study are typically fed into a simulator (Green and
Krieger 1988) to obtain individual level choice shares for alternative product designs. The logit model is a widely used conjoint simulator.

The traditional approach to new product introduction or product repositioning decision identifies a design which is conditional on the respondent always making a purchase from the product category. In a typical conjoint simulator, it is assumed that the respondent will actually purchase the preferred design. The conceptual problem with such an approach is that it excludes the purchase/non-purchase decision from the analysis. The potential buyers and non-buyers are treated in an identical fashion. By doing so, the analysis also ignores any opportunity a firm might have to attract new buyers to the product category. Two pieces of information with respect to purchase quantity are relevant. First, will the respondent actually purchase the product? And second, how much of the product will the consumer buy? It is through this quantity related information that I will establish the link between product design and primary demand of the product.

The conjoint literature lacks a framework to formally include purchase quantity in analysis relating to product design. Sawtooth Software Inc.’s Choice Based Conjoint(CBC) is the only conjoint based approach that collects information about purchase/non-purchase of the product profiles presented. This is accomplished by giving the respondents the option of not choosing any of the available choice alternatives. The CBC approach, however, has two limitations. First, it does not model purchase quantity in its specification. Second, it does not provide individual level estimates.
In this research, I present a formal framework based upon economic theory which establishes a link between product design and primary demand. An estimation procedure which overcomes limitations of Sawtooth's CBC is developed.

3. Discrete/Continuous Models

<table>
<thead>
<tr>
<th>Reference</th>
<th>Economic model</th>
<th>Joint modeling of brand choice and purchase quantity</th>
<th>Reservation Value</th>
<th>Product Design and Primary Demand</th>
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<tbody>
<tr>
<td>Guadagni and Little 1983</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
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<tr>
<td>Neslin, Henderson and Quelch 1985</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
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<tr>
<td>Gupta 1988</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Krishnamurthy and Raj 1988</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
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<tr>
<td>Hanemann 1984</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Chiang 1991</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes, Aggregate</td>
<td>No</td>
</tr>
<tr>
<td>Chintagunta 1993</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes, Aggregateb</td>
<td>No</td>
</tr>
<tr>
<td>This research</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes, Individual</td>
<td>Yes</td>
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</table>

a: Utility maximization for discrete and continuous decisions.
b: Allows for heterogeneity across the population.

As stated earlier, a majority of marketing models have focused on either the brand choice (e.g. Guadagni and Little 1983) or purchase quantity (e.g. Neslin, Henderson and Quelch 1985) issue. Gupta (1988) was the first to study consumer decisions of whether
to buy, which brand to buy and how much to buy in a single study. The unique feature of Gupta's work is that he models purchase timing along with brand choice and purchase quantity. However, his modeling approach did not jointly model these three decisions under a single utility maximizing framework. Krishnamurthy and Raj (1988) present a statistical argument of parameter consistency and efficiency in support of jointly modeling brand choice and purchase quantity.

Chiang (1991) and Chintagunta (1993) used an economic framework of utility maximization under a budget constraint to jointly model two consumer decisions namely, brand choice and purchase quantity. Motivated by Hanemann's (1984) work on discrete/continuous models, these authors use a microeconomic framework to jointly model the two consumer decisions. Both utilize the notion of reservation value (or reservation price) to explain whether a consumer buys or does not buy an item from a product category. The distinction between Chiang (1991) and Chintagunta (1993) is that the former estimates a single aggregate (group level) reservation value whereas the latter estimates a distribution of heterogeneity across the sample for the reservation value. Also, the latter is different as it assumes a constant price coefficient across individuals.

Next, I outline Gupta (1988), Krishnamurthy and Raj (1988), Hanemann (1984), Chiang (1991) and Chintagunta (1993) in some detail as their work is directly relevant to the proposed research.
(i) Gupta (1988):

Gupta (1988) considers the brand choice and the purchase quantity decision to be conditional on the purchase timing decision. The three consumer decisions of brand choice, purchase timing\(^1\) and purchase quantity are modeled as follows. The brand choice probability is given by:

\[
P_{ijn} = \frac{\exp (b'X_{ijn})}{\sum_m \exp (b'X_{imn})} \tag{1}
\]

\(P_{ijn}\) is the probability that person \(i\) buys brand \(j\) on the \(n\)th purchase occasion.\(X_{ijn}\) is the set of independent variables for brand \(j\) and consumer \(i\) on the \(n\)th purchase occasion and \(b\) is the response coefficient vector corresponding to \(X_{ijn}\).

The quantity decision is modeled as follows. Quantity \(Q\) is treated as an ordered categorical variable having \(k = 1, \ldots, L\) possible values. Let \(Q\) have an underlying latent variable \(V\) with interval scale properties\(^2\). Further, let \(V\) be modeled as a linear function of \(Z\), a vector of household specific variables such as inventory.

\[
V = \beta'Z + \epsilon \tag{2}
\]

It is then possible to relate observed quantity \(Q\) to the unobservable latent variable \(V\) through some unknown cutoff points \(\theta_k\). The purchase quantity can be viewed as

\(^1\)The issue of purchase timing is not addressed in this dissertation.

\(^2\) This is analogous to relating consumer choice to the utility of an alternative in a random utility model.
where \( \theta_k \) is an unknown cutoff point such that

\[-\infty = \theta_0 < \theta_1 < \theta_2 < \ldots \theta_{L-1} \leq \theta_L = \infty\]

Assuming a logistic distribution for \( \varepsilon \),

\[
P(Q_{im} \leq k) = \frac{\exp (\theta_k - \beta'Z_{im})}{1 + \exp (\theta_k - \beta'Z_{im})} \tag{4}
\]

where \( Q_{im} \) is the quantity that consumer \( i \) buys on purchase occasion \( n \). \( Z_{im} \) is the set of independent variables with \( \beta \)'s as the corresponding response coefficients. This leads to

\[
P(Q_{im} = k) = P(Q_{im} \leq k) = P(Q_{im} \leq k-1) \tag{5}
\]

The non-standard form for the quantity equation is motivated by the fact that quantity is an ordered categorical variable with \( k=1,\ldots,L \) possible values.

For person \( i \), the interpurchase time is given by

\[
f_{iw}(t) = \alpha_{iw}^2 t \exp(-\alpha_{iw} t) \tag{6}
\]
where \( f_{iw}(t) \) is the pdf of interpurchase time \( t \) in week \( w \). The unit of analysis for interpurchase time is weeks. \( \alpha_{iw} \) is a scale parameter and is defined as

\[
\alpha_{iw} = \exp(-c'Y_{iw})
\]  

(7)

\( Y_{iw} \) is the vector of independent variables to explain the mean interpurchase time with \( c \) being the vector of response coefficients.

The author used IRI (Information Resources Inc.) scanner panel data for coffee to calibrate and validate the above model. He found that most of the increase in sales caused by a promotion is due to brand switching (84%). Purchase acceleration accounts for 14% and stockpiling accounts for 2% of the sales increase.

Since the author’s analysis is carried out at the aggregate level, no inference can be drawn at the individual level. Questions such as “who are the new coffee consumers that a price promotion brings to the market?” or “who are the consumers with the largest increase in expected quantity because of a price promotion?” are not investigated. These questions are addressed in this dissertation.

(ii) Krishnamurthy and Raj (1988)

The authors argue that it is incorrect to model brand choice and purchase quantity decision independently since the two are inter-related. Separate modeling of these inter-related consumer decisions leads to biased and inconsistent regression estimates for the quantity equation and inefficient estimates for the choice equation. The approach adopted by the authors to counter this problem is as follows:
For person $i$, let $I_i^*$ represent the latent utility corresponding to an alternative with characteristics $Z_i$. Then

$$I_i^* = Z_i^\gamma - \epsilon_i$$  \hspace{1cm} (8)

where $\gamma$ is the vector of choice parameters and $\epsilon_i$ is the random error. Consider a binary choice case where $y_{1i}$ and $y_{2i}$ reflect the quantity bought for alternatives 1 or 2. Further, let $I_i=1$ when alternative 1 is chosen and 0 otherwise. The latent utility can be rescaled such that $I_i=1$ when $I_i^*>0$ and $I_i=0$ when $I_i^*<0$. Then one can write:

$$Y_{1i} = X_{1i}\beta_1 + u_{1i}, \text{ iff } \epsilon_i \leq Z_i^\gamma, \text{ i.e. } I_i = 1$$
$$Y_{2i} = X_{2i}\beta_2 + u_{2i}, \text{ iff } \epsilon_i > Z_i^\gamma, \text{ i.e. } I_i = 0$$  \hspace{1cm} (9)

where $\beta_1$ and $\beta_2$ are regression parameters and $u_{1i}$ and $u_{2i}$ are the error terms. If the choice error $\epsilon_i$ is correlated with $u_{1i}$ and $u_{2i}$ then the conditional expectations of $u_{1i}$ and $u_{2i}$ are non-zero. Therefore, if OLS is used to estimate the quantity equations, the corresponding estimates are biased and inconsistent.

The authors suggest a "corrected" disturbance term to obtain

$$Y_{1i} = X_{1i} \beta_1 - \alpha_1 S_{1i} + v_{1i}$$
$$Y_{2i} = X_{2i} \beta_2 - \alpha_2 S_{2i} + v_{2i}$$  \hspace{1cm} (10)

where $S_{1i}$ and $S_{2i}$ are "selectivity bias" correction terms which are dependent upon $Z_i^\gamma$.

The discrete choice equation is therefore linked with purchase quantity equation through a selectivity bias term in the latter.
The authors calibrate the above model using data from an ADTEL diary panel for a frequently purchased product class. They showed that a price change affects brand choice as well as quantity. They were able to obtain estimates for choice elasticities and quantity elasticities for different brands and the estimates reflected that these elasticities varied by brand. The authors use a demographic variable such as income as an independent variable for utility in order to account for differences across individuals. However, since the authors' analysis is at the aggregate level, one can not infer how response coefficients vary by individuals.

(iii) Hanemann (1984)


For an individual with demographic characteristics s, the utility function over choices \( w = \{w_1, w_2, \ldots, w_n\} \) with attributes \( x = \{x_1, x_2, \ldots, x_n\} \) may be written as \( u(w, x, w_{n+1}, s) \). Here \( w_{n+1} \) is a composite good representing all goods other than \( w \) that the consumer may buy. The composite good has a unit price. The objective function of the consumer is to maximize \( u(w, x, w_{n+1}, s) \) subject to a budget constraint \( y \), i.e.

\[
\begin{align*}
\text{Max.} & \quad u(w, x, w_{n+1}, s) \\
\text{subject to} & \quad \sum_j p_j w_j + w_{n+1} = y, \\
& \quad w_j \geq 0 \text{ for all } j = 1, \ldots, n \text{ and} \\
& \quad w_{n+1} > 0
\end{align*}
\]
The \( w_j \)'s are treated as perfect substitutes, i.e. the utility function has to be such that indifference curves for pairs of \( w_j \)'s are linear or concave. This ensures that only one of the \( w_j \)'s gets chosen. One such functional form is the conventional bivariate utility function, i.e.

\[
    u(w, x, w_{n+1}, s) = u \left( \sum \psi_j w_j, w_{n+1} \right)
\]

where \( \psi_j \) is a perceived quality index for brand \( j \). The first argument on the right hand side of equation (12) ensures linear indifference curves between choices in \( w \). This results in only one item being chosen from \( w \). Given that a consumer chooses brand \( j \), the corresponding conditional direct utility is

\[
    \bar{u}_j = u \left( \psi_j w_j, w_{n+1} \right)
\]

In microeconomics, it is conventional to rewrite the direct utility function in (13) in terms of an indirect utility function. Unlike the direct utility function, the indirect utility function is a function of price and income constraint (Varian 1984) in addition to the perceived quality index. From equations (11) and (13) it can be shown that the indirect utility function is

\[
    \bar{v}_j = v \left( \frac{\psi_j}{P_j}, y \right)
\]
Since \( v^* \) is a decreasing function of \( p_j/\psi_j \), the single brand chosen is the one which has the lowest \( p_j/\psi_j \). If \( \psi_j \) is assumed to be stochastic, then the discrete choice probability corresponding to brand \( j \) is

\[
\pi_j = Pr \left( \ln p_j - \ln \psi_j \leq \ln p_i - \ln \psi_i, \text{ for all } i \right) \quad (15)
\]

If we let

\[
\psi_j = \exp(x_j \beta + \epsilon_j), \text{ where } \epsilon_i \sim EV(\mu,0); \mu > 0 \quad (16)
\]

then

\[
\pi_j = Pr \left( x_j \beta_j - \ln p_j + \epsilon_j \geq x_i \beta_i - \ln p_i + \epsilon_i, \text{ for all } i \right) \quad (17)
\]

or

\[
\pi_j = \frac{\exp \left( x_j \beta_j - \ln p_j / \mu \right)}{\sum_k \exp \left( x_k \beta_k - \ln p_k / \mu \right)} \quad (18)
\]

One way to relate choice outcome data to model parameters is to map the information contained in the data into a region in which the error term for the chosen alternative lies. That is, if alternative \( j \) is chosen then error \( \epsilon_j \) lies in the region \( A_j \) where

\[
A_j = \{ \epsilon \mid \epsilon_j + x_j \beta - \ln p_j \geq \epsilon_i + x_i \beta - \ln p_i, \text{ for all } i \} \quad (19)
\]
Hanemann then shows that the conditional distribution of \( \varepsilon_j \) given that \( j \) is the chosen alternative is then given by

\[
f_{\varepsilon_{j|j}}(\varepsilon_j) \sim EV (\mu, \mu \ln(\pi_j)^{-1})
\]

Next, this conditional pdf of the error term of the chosen alternative can be used to obtain the pdf of the quantity \( w_j \) of the chosen alternative. This is accomplished by the variable transformation method. If \( w_j = g(p_j, x_j, y_j, \varepsilon_j) \) then the pdf of the quantity \( w_j \) can then be obtained as follows

\[
f_{w_{j|j}}(w_j) = f_{\varepsilon_{j|j}}(g^{-1}(w_j)) \cdot \left| \frac{\partial}{\partial w_j} \left( g^{-1}(w_j) \right) \right|
\]

Note that the functional form of \( g(.) \) determines the pdf of \( w_j \).

The elegant feature of Hanemann’s formulation is that it captures the discrete choice outcome and the continuous quantity outcome in a single framework using micro-economic theory. This allows for a simultaneous estimation of choice and quantity related parameters in the model. Chiang(1991) and Chintagunta(1993) build upon Hanemann’s framework to study marketing problems.

(iv) Chiang (1991)

Chiang (1991) uses a microeconomic framework to simultaneously model quantity and brand choice. Like Hanemann (1984), he uses a bivariate utility function:

\[
u (\sum_j \psi_j w_j, \psi_{n+1} w_{n+1})
\]
The consumer objective function then is to maximize u subject to the budget constraint.

Chiang considers two cases:

Case 1: Non-purchase

The consumer does not buy if \( \min (p_j/\psi_j \text{ for all } j) > c \), a cut-off point.

Case 2: Purchase

The consumer chooses brand h if

\[ p_h/\psi_h = \min (p_j/\psi_j, j=1,...,N) \text{ and } p_h/\psi_h < c. \]

Based upon Christenson, Jorenson and Lau (1975), he uses a translog utility function to derive the demand equation for brand j. In the translog specification, if \( S \) is the expenditure share for the chosen brand j, then it can be shown that

\[ S = -\alpha_1 - \beta_{11} \ln \frac{P_j}{\psi_j} + \beta_{11} \ln \frac{P_{k+1}}{\psi_{k+1}} \]

(23)

The share is restricted to be positive, i.e. there exists a threshold level \( c \) such that the consumer buys from the given product category if \( p_j/\psi_j \) is below the cut-off \( c \). By setting \( S=0 \) in equation (23) the cut-off \( c \) is given by:

\[ c = \exp(-\alpha_1/\beta_{11}) \frac{P_{k+1}}{\psi_{k+1}} \]

(24)

Like Hanemann, he defines the perceived quality index \( \psi_j \) for brand j as

\[ \psi_j = \exp (x_j \beta_j + \epsilon_j) \]

(25)
where \( x_j \) includes marketing mix variables and consumer demographic characteristics. The errors \( \epsilon_j \) are assumed to be distributed generalized extreme value and are iid across individuals. Also,

\[
\Psi_{k+1} = \exp(\epsilon_{k+1})
\]  

(26)

where \( \epsilon_{k+1} \) is extreme value with location parameter modeled as a function of demographics in order to reflect consumer heterogeneity. The distributional assumptions outlined above allow him to derive closed form expressions for choice probability and probability of non-purchase.

The unique contribution of Chiang's paper is the introduction of the notion of reservation value (or price). The proposed model is therefore not conditional on purchase. This allows for computation of a probability of buying or not buying at the aggregate level. In addition the author is able to obtain an aggregate level demand equation for quantity purchased. No inference at the individual level is feasible however.

(v) Chintagunta (1993)

Chintagunta also developed a model based upon a micro-economic framework which jointly maximizes a consumer's utility for the two decisions of which brand to buy and how much to buy. The author points out that models which attempt to relate brand choice with marketing mix variables by using only purchase data do not use the entire information available. The shopping trips of a consumer in which s/he does not make a purchase from the category of interest can be used to understand an individual's
reservation price (utility) for the item. This can then be used to compute an individual's probability of purchase and non-purchase. The effect of consumer stockpiling on purchase in this set-up is captured by treating household inventory as an independent variable in the computation of utility.

According to the author, models which do not incorporate non-purchase data therefore can be called 'conditional on sales' models since they ignore those shopping trips of consumers in which they do not buy from the product category. He argues that individual level non-purchase data corresponding to those shopping trips when a given consumer does not purchase a brand from the category of interest should also be used in modeling a consumer's behavior. This is because 'conditional-on-sale' analysis could potentially overstate the magnitude of consumer response to promotions and other marketing mix variables.

The author presents an 'unconditional on sale' model which explicitly captures the probability of non-purchase. He also derives expressions for choice probability and purchase quantity. Like Chiang (1991) and Hanemann (1984), he specifies a utility maximizing framework subject to an income constraint. Similar to Chiang's paper, he uses the notion of reservation price. He treats reservation price as an "unobservable, household specific and time invariant". He specifies and estimates parametric and non-parametric functional forms of distributions for reservation price heterogeneity. In addition, he also estimates a distribution of heterogeneity for brand preferences.
For store visit $t = 1, \ldots, T$; household $i = 1, \ldots, M$; and brand $j = 1, \ldots, N$, the author derives the following expressions:

a. Purchase probability:

If $R_i$ is the reservation price for person $i$, then the probability of actually making a purchase ($B_{it}=1$) is given by

$$Pr (B_{it} = 0) = \exp \left( - R_i \sum_j \exp (\lambda_{ij}) \right)$$

(27)

where

$$\lambda_{ij} = \gamma_j + \sum_s X_{ijst} \beta_s - \ln p_{ijt}$$

(28)

For household $i$, at time $t$, $\gamma_j$ is the preference for brand $j$, $X_{ijst}$ is the value of the $s$th quality attribute, $\beta_s$ is regression coefficient and $p_{ijt}$ is the price.

b. Choice probability

Choice probability that person $i$ chooses alternative $j$ at time $t$ ($D_{it}=j$) is

$$Pr (D_{it} = j \mid B_{it} = 1) = \frac{\exp v_{ij}}{\sum_k \exp v_{ikr}}$$

(29)

$v_{ij}$ is the same as $\lambda_{ij}$ except $X_{ij}$ does not contain variables that are constant across brands.

Therefore for person $i$ at time $t$, the joint probability of choosing brand $j$ ($D_{it}=j$) and actually making a purchase ($B_{it}=1$) is

$$Pr (D_{it}=j , B_{it}=1 ) = Pr (B_{it}=1 ) * Pr (D_{it} = j \mid B_{it} = 1 )$$

(30)
c. Quantity equation:

Hanemann (1984) suggests several different functional forms for the indirect utility functions which lead to tractable demand models. One such functional form is

\[ v \left( \frac{p_{yt}}{\psi_{yt}}, y_{yt} \right) = (y_{yt} + \theta_1 \frac{p_{yt}}{\psi_{yt}} + \theta_2 \left( \frac{p_{yt}}{\psi_{yt}} \right)^{-\eta} \right) \]

(31)

Using Roy's identity, the corresponding demand equation is:

\[ p_{yt} E(Q_{yt}) = \eta \theta_2 + \eta y_{yt} - (1 - \eta) \theta_1 \left[ \Sigma_k \exp (\lambda_{kt}) \right] \]

(32)

Where \( \eta, \theta_1, \) and \( \theta_2 \) are parameters that need to be estimated. These parameters have the following interpretation:

\( \eta \) = sensitivity of quantity purchased to shopping expenditure.

\( \theta_2 \) = average expenditure on product category of interest, conditional on a purchase being made from the category.

\( \theta_1 \) = effect of independent variables such as price and product attributes on the quantity decision.

The author uses A.C. Neilsen data on the purchase of yogurt to calibrate the model. He concludes that the unconditional brand choice elasticities are larger in magnitude than conditional ones. This provides empirical evidence of an increase in primary demand as a consequence of marketing mix changes. Also, the author points out that estimated model parameters may be biased if heterogeneity among consumers is not considered. His model recognizes heterogeneity among consumers with respect to
reservation utility and brand preference. Inference at the individual level is however not feasible in the author’s approach since the model does not estimate individual level parameters.

4. Contribution of this Research

Based upon the review of literature in parts 1, 2 and 3 of this chapter, this research makes a significant methodological and substantive contribution to the marketing literature. The first methodological contribution of the dissertation is that it provides individual level estimates of reservation value and expenditure sensitivity parameters. The reservation value relates product design to the purchase/non-purchase decision of an individual and the expenditure sensitivity parameter relates product design to the purchase quantity of an individual. The second methodological contribution is to establish a link between conjoint methodology and the consumer decision of purchase/non-purchase and purchase quantity. Traditionally, the use of conjoint analysis has been restricted to understanding the consumer choice decision only. By combining microeconomic theories with conjoint analysis, this dissertation studies the two consumer decisions of what to buy and how much to buy in a single unifying framework.

The substantive contribution of the dissertation is that it provides a formal framework to understand the link between product design and primary demand. From a brand manager’s perspective, the framework assists in developing a product design strategy which increases the market share as well as the market size. Analysis at the individual level helps in identifying those consumers who have the largest potential to increase primary demand. A demographic, attitudinal or behavioral profile of these
consumers can be used for targeting purposes. The framework is therefore useful for product introduction and/or product repositioning decisions. This is a significant improvement over our current state of knowledge on the topic of primary demand as the existing research is limited to aggregate level empirical investigation of the effect of advertising and price on primary demand.
CHAPTER III

Theory

This chapter is divided into three parts. Part 1 provides background information on the translog utility function. This utility function is an important component of the model specification. Part 2 discusses the model specification. Part 3 provides details about the estimation procedure and the related distribution theory for the model specified in part 2.

1. Background: Translog Utility Function

For a given consumer, consider a direct utility function

\[ \ln U = \ln U (q(1)\psi(1), \ldots, q(m)\psi(m)) \]  \hspace{1cm} (33)

where for good \( j \), \( q(j) \) is the quantity consumed, \( \psi(j) \) is the quality index and \( p(j) \) is the price. There are \( m \) goods in this utility specification \( (j=1,\ldots,m) \). The consumer objective function is to Maximize \( (\ln U) \) subject to \( \Sigma_j p(j) q(j) = M \). \( M \) is the budget constraint.

Consider the functional form for the translog utility function (Christenson, Jorenson and Lau 1975, Chiang 1991)

\[ -\ln U = \alpha_0 + \Sigma_j \alpha_j \ln (q(j)\psi(j)) + \frac{1}{2} \Sigma_j \Sigma_k \beta_{jk} \ln (q(j)\psi(j)) \ln (q(k)\psi(k)) \]  \hspace{1cm} (34)
This can be viewed as a second order Taylor series approximation in which constraints are placed on parameters $\alpha_j$ and $\beta_{jk}$ to ensure consistency with known properties of demand functions. In microeconomics, it is conventional to rewrite the direct utility function in equations (33) and (34) in terms of an indirect utility function. Unlike the direct utility function, the indirect utility is a function of good prices and the income constraint (Varian 1984, p.116). An individual’s indirect utility is the maximum achievable utility at a given price $p(j)$ ($j=1,...,m$) and income. For good $j$, the value of quantity $q(j)$ that solves the indirect utility function is the consumer’s demanded bundle at the given price $p(j)$ and income. A demand function relates price $p(j)$ to the quantity $q(j)$.

The key advantage of using the translog utility function in this dissertation is that it leads to a tractable demand function (also see Chiang 1991).

The indirect utility function ($V$) for the translog utility function is given by

$$
\ln V = \alpha_0 + \sum_j \alpha_j \ln \frac{p(j)}{\psi(j)M} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln \frac{p(j)}{\psi(j)M} \ln \frac{p(k)}{\psi(k)M}; \ j, k = 1,...,m
$$

(35)

From the indirect utility function above, the demand function in terms of expenditure share $s(j)$, can be obtained by using the logarithmic form of Roy's identity (Varian 1984, p.126):

$$
s(j) = \frac{p(j)q(j)}{M} = -\frac{\partial \ln V}{\partial \ln p(j)} / \frac{\partial \ln V}{\partial M}
$$

(36)

or
\[ s(j) = \frac{\alpha_j + \sum_k \beta_{jk} \ln \frac{p(k)}{\psi(k)M}}{\alpha_M + \sum_k \beta_{Mk} \ln \frac{p(k)}{\psi(k)M}} \]  

(37)

where

\[ \alpha_M = \sum_j \alpha_j \text{ for } j = 1, 2, \ldots, m \; ; \; \beta_{Mk} = \sum_l \beta_{lk} \text{ for } l, k = 1, \ldots, m \]  

(38)

Derivations for the above are available in Christenson, Jorgenson and Lau (1975).

Since expenditure shares should add up to 1, some form of normalization is required for the purpose of estimation. Christenson et al suggest

\[ \alpha_M = \sum_j \alpha_j = -1 \]  

(39)

Also, since the function \( \ln (V) \) is homogenous of degree zero (see Christenson, Jorgenson and Lau 1975, Chiang and Lee 1992),

\[ \beta_{Mk} = \sum_k \beta_{lk} = 0 \text{ for } k, l = 1, \ldots, m \]  

(40)

Therefore, the expression for the demand function in terms of the expenditure share \( s(j) \) in equation (37) reduces to

\[ s(j) = -\alpha_j - \sum_k \beta_{jk} \ln \frac{p(k)}{\psi(k)M} \]  

(41)
2. Model Specification

As stated earlier, the key advantage of using the translog utility function is that it leads to a tractable demand function (equation 41). Next, I will use this function to develop a unifying framework to model brand choice and purchase quantity decisions of a consumer (also see Chiang 1991). Model development involves three main steps. First a logit-type expression for choice probability is obtained. Second, a density function for the utility per dollar of the chosen alternative is derived. And third, expressions which relate consumer purchase/non-purchase and quantity decisions to the utility per dollar of the chosen alternative are developed.

(i) Choice Probability:

For a given consumer consider a bivariate utility function:

\[ u = \left( \sum_j \psi(j) q(j), \psi(m+1) q(m+1) \right) \]  

(42)

For the given purchase occasion, let there be \( m \) alternatives (i.e. \( j=1,...,m \)) in the product category available to the consumer. All products outside of the product category of interest are treated as a composite good \((m+1)\) and the composite good is essential to the consumer (i.e. \( q(m+1) > 0 \)). The linearity of the first argument in equation (42) results in linear indifference curves. This ensures a corner solution to the utility maximization

---

3 Theory at this stage is developed for a given consumer on a given choice occasion. Indices \( i=1,...,h \) for persons and \( t=1,...,T \) for purchase occasions are suppressed for the sake of clarity. These will be introduced in the section on hierarchical model, estimation procedure and distribution theory.
problem. Therefore the model assumes that a consumer chooses only one alternative and
the available alternatives are perfect substitutes.

For such a case, if j is the chosen brand from a choice set of m, the corresponding
indirect utility function from equation (35) is

\[ v(j) = \alpha_0 + \alpha_1 \ln \frac{p(j)}{\psi(j) M} + \alpha_2 \ln \frac{p(m+1)}{\psi(m+1) M} + \frac{1}{2} \beta_{11} (\ln \frac{p(j)}{\psi(j) M})^2 + \frac{1}{2} \beta_{22} (\ln \frac{p(m+1)}{\psi(m+1) M})^2 \]

\[ + \frac{1}{2} \beta_{12} \ln \frac{p(j)}{\psi(j) M} \ln \frac{p(m+1)}{\psi(m+1) M} \]

(43)

Since \( v(j) \) is decreasing in \( p(j)/\psi(j) \), it follows that consumer chooses the brand for which
\( p(j)/\psi(j) \) is lowest. Consumer choice \( \delta(j) \) is given by

\[ \delta(j) = 1 \quad \text{if} \quad \frac{p(j)}{\psi(j)} \leq \frac{p(k)}{\psi(k)} \quad \text{for all} \quad k, \]

\[ = 0 \quad \text{otherwise} \]

(44)

where \( \delta(j)=1 \) means that brand j is chosen. Next, define the quality index \( \psi(j) \) to be
related to product attributes \( x(j) \) as follows:

\[ \psi(j) = \exp (x(j) \beta + \epsilon(j)) \]

(45)

where, \( \beta \) is the vector of regression coefficients and \( \epsilon(j) \) is the random error. The choice
probability \( Pr(j) = E(\delta(j)) \), can then be written as

\[ Pr(j) = Pr \left( \frac{\psi(j)}{p(j)} \geq \frac{\psi(k)}{p(k)} \quad \text{for} \quad k=1,...,m \right) \]

(46)
Or,

$$Pr(j) = Pr \left( x(j)\beta - \ln p(j) + \varepsilon(j) \geq x(k)\beta - \ln p(k) + \varepsilon(k), \text{ for } k=1,...,m \right)$$  \hspace{1cm} (47)

Next define $y(j)$, the log of quality index for brand $j$ per unit price as the utility per dollar. Since $y(j) = x(j)\beta - \ln p(j)$, equation (47) can be rewritten as

$$Pr(j) = Pr \left( y(j) + \varepsilon(j) \geq y(k) + \varepsilon(k), \text{ for all } k=1,...,m \right)$$  \hspace{1cm} (48)

I assume that $\varepsilon(j)$ is iid $EV(\mu, 0), \mu > 0$. Here $\mu$ is the scale parameter of the extreme value distribution. Given this assumption, Hanemann (1984) shows that

$$Pr(j) = \frac{\exp \left( y(j) \right)}{\mu} \frac{\mu}{\sum_k \exp \left( \frac{y(k)}{\mu} \right)}$$  \hspace{1cm} (49)

The quantity $1/\mu$ is the coefficient of log price in equation (49) and can therefore be interpreted as a measure of price sensitivity. Higher the value of $\mu$, lower is the price sensitivity.

(ii) Density function for the utility per dollar of the chosen alternative:

One way to relate choice outcome data to model parameters is to map the information contained in the data into a region in which the error term for the chosen alternative lies. That is, if alternative $j$ is chosen then error $\varepsilon_j$ lies in the region $A_j$ where

$$A_j = \{ \varepsilon | \varepsilon(j) + x(j)\beta - \ln p(j) \geq \varepsilon(k) + x(k)\beta - \ln p(k), k=1,...,m \}$$  \hspace{1cm} (50)
The conditional distribution of the error term \( \varepsilon_j \) given \( j \) is the chosen alternative is then given by

\[
f_{\varepsilon_j | \varepsilon_j}(\varepsilon(j)) = \frac{F_{\varepsilon}^{\prime}(\varepsilon(j) + y(j) - y(1), \ldots, \varepsilon(j) + y(j) - y(m))}{Pr(j)}
\]

where \( F_{\varepsilon}^{\prime} \) is the partial derivative of the joint cdf \( F_{\varepsilon}(\cdot) \) of the error terms with respect to the \( j \)th argument. It is shown by Hanemann (1984) that

\[
\begin{align*}
    f_{\varepsilon_j | \varepsilon_j}(\varepsilon(j)) & = EV(\theta, \xi) \\
    \theta & = \mu; \quad \xi = \mu \ln \frac{1}{Pr(j)}
\end{align*}
\]

This is the conditional pdf of the error term of the chosen alternative. The expected value of the error term in equation (52) is \( \mu(\ln 1/Pr(j) + 0.57722) \). This suggests that the expected error is small when a high probability alternative is chosen. However, when the observed choice is "surprising", i.e. a low probability alternative is chosen then the expected error is large. This is consistent with what one should expect. The cdf corresponding to equation (52), evaluated at \( \varepsilon(j) = k \) is (Johnson and Kotz, p.278)

\[
F(k) = \exp(-\exp(\frac{\xi - k}{\theta}))
\]

As will be seen shortly, it is through the conditional pdf in equation (52) that the demand equation is related to the utility per dollar, \( y(\cdot) \) of an alternative. From the indirect utility function (eqn. 43), the demand function in terms of expenditure share equation (eqn. 41) is given by
\[ s(j) = \frac{p(j)q(j)}{M} = -\alpha_1 - \beta_{11} \ln \frac{p(j)}{\psi(j)} + \beta_{11} \ln \frac{p(m+1)}{\psi(m+1)} \]  

(54)

This can be re-written as

\[ p(j)q(j) = s(j) = \alpha^* + \beta_x \ln \frac{\psi(j)}{p(j)} \]  

(55)

where

\[ \alpha^* = -\alpha_1 M + \beta_{11} \ln \frac{p(m+1)}{\psi(m+1)} * M \quad \text{and} \]
\[ \beta_x = -\beta_{11} M \]  

(56)

From equation (55), the definition of \( \psi(j) \) in equation (45) and the definition of

\[ y(j) = x(j) \beta - \ln p(j), \]

\[ s(j)^* = \alpha^* + \beta_x (\ln \psi(j) - \ln p(j)) \], or
\[ s(j)^* = \alpha^* + \beta_x \bar{y}(j) \]  

(57)

where

\[ \bar{y}(j) = y(j) + \epsilon(j) \]  

(58)

From equations (52) and (58), it is seen that \( \bar{y}(j) \) has well defined distributional properties, i.e.

\[ \bar{y}(j) \sim EV(\Theta', \xi'); \quad \Theta' = \mu \quad \text{and} \quad \xi' = \mu \ln \frac{1}{p(r(j))} + y(j) \]  

(59)
(iii) Purchase/non-purchase and quantity as a function of utility per dollar

Note that at

$$s(j)^* = 0, \quad y(j) = -\frac{\alpha^*}{\beta_s}$$  \hspace{1cm} (60)

The quantity $-\alpha/\beta_s^*$ is called the reservation value, $y_{cut}$. Purchase quantity is zero when $y(j)$ is less than $y_{cut}$ and is non-zero when $y(j)$ is greater than $y_{cut}$. The parameter $y_{cut}$ is set to zero such that the estimated values of $y(j)$'s are relative to a $y_{cut}$ of zero. Also, note that the observed purchase quantity $q(j)$ can be related to the model parameters $\alpha^*$ and $\beta_s$ in the following way:

(1) when $q(j) = 0$ then

$$\tilde{y}(j) < -\frac{\alpha^*}{\beta_s} + 0.5 * \frac{p(j)}{\beta_s}$$  \hspace{1cm} (61)

(2) when $q(j) = 1$ then

$$-\frac{\alpha^*}{\beta_s} + 0.5 * \frac{p(j)}{\beta_s} < \tilde{y}(j) < -\frac{\alpha^*}{\beta_s} + 1.5 * \frac{p(j)}{\beta_s}$$  \hspace{1cm} (62)

(3) when $q(j) = 2$ then

$$-\frac{\alpha^*}{\beta_s} + 1.5 * \frac{p(j)}{\beta_s} < \tilde{y}(j) < -\frac{\alpha^*}{\beta_s} + 2.5 * \frac{p(j)}{\beta_s}$$  \hspace{1cm} (63)
In general, when \( q(j) = q \) (for \( q > 0 \)), then

\[
- \frac{\alpha^*}{\beta_s} + (q - 0.5) \frac{p(j)}{\beta_s} < \gamma(j) < - \frac{\alpha^*}{\beta_s} + (q + 0.5) \frac{p(j)}{\beta_s}
\]  \( (64) \)

The quantity \( 1/\beta_s \) is referred to as \( \kappa \). It provides a measure of an individual’s expenditure sensitivity to the product utility. Higher the value of \( \kappa \), lower is an individual’s expenditure sensitivity. Therefore, individuals with low \( \kappa \) are more likely to increase their expenditure in response to changes in a product’s design.

From equation (64), the probability of quantity \( q(j) = q \) given \( j \) is the chosen alternative is:

\[
Pr(q | j) = F_{\gamma}^{-1} (0.5 * p(j) * \kappa) \text{ for } q(j) = 0
= F_{\gamma}^{-1} ((q(j) + 0.5)p(j) \kappa) - F_{\gamma}^{-1} ((q(j) - 0.5)p(j) \kappa) \text{ for } q(j) > 0
\]  \( (65) \)

where \( F_{\gamma}(\cdot) \) is the cdf of an extreme value distribution with parameters defined by equation (59).

3. Hierarchical model, Estimation procedure and Distribution theory

The objective of this dissertation is to obtain individual level estimates of partworths, expenditure sensitivity and price sensitivity. Having developed the theory in the previous section, next I outline a procedure to estimate the model. The proposed procedure is based upon a hierarchical Bayes model and uses a simulation based method called Gibbs sampling (Geifand and Smith 1990). Hierarchical models and Gibbs sampling have been used by Allenby and Lenk(1995), Allenby, Arora and Ginter(1995),...
and Allenby and Ginter(1995) for marketing applications. Gibbs sampling is a relatively new computational method and is now being used widely to estimate hierarchical Bayes models. The hierarchical model, estimation procedure and the associated distribution theory follow.

Let i=1,...,h be the index for person, \( t=1,...,T \) be the index for purchase occasion and \( j=1,...,m \) be the index for choice alternative. Let there be k non-price attributes in each choice alternative. Then the model follows the following hierarchical structure:

\[
[N,Y,X,\alpha,\Sigma, \beta] [Y|X,\alpha,\beta,\Sigma] [\beta|D] [\Sigma|D] [\mu|\lambda_\mu] [\lambda_\mu|\rho_\mu,\tau_\mu][\tau_\mu][\kappa|\lambda_\kappa] [\lambda_\kappa|\rho_\kappa,\tau_\kappa][\tau_\kappa]
\]

where:

\( N = \) \((T \times h)\) matrix of choice data indicating the alternative chosen
\( Q = \) \((T \times h)\) matrix of quantity data of the chosen brand
\( X = \) \(\{X(1),...,X(m)\}\) where \(X(j)\) is a \((T \times kh)\) matrix of attributes of the \(j\)th alternative
\( Y = \) \(\{Y(1),...,Y(m)\}\) where \(Y(j)\) is a \((T \times h)\) matrix of utilities corresponding to \(X(j)\)
\( \alpha = \) \((k \times 1)\) vector of mean of the regression coefficients (partworths) across the sample
\( \{\beta_i\} = \\{\beta_{1i},...\beta_{hi}\}\) where \(\beta_i\) is a \((k \times 1)\) vector of deviations from \(\alpha\) for individual \(i\).
\( \Sigma = \) covariance matrix for the error terms in the regression equation
\( D = \) \((k \times k)\) covariance matrix for the distribution of heterogeneity of the regression coefficients
\( \{\mu_{ui}\} = \) \((T \times 1)\) vector of scale parameter of the extreme value distribution for person \(i\)
\( \lambda_u = \) \((h \times 1)\) vector of parameters for the exponential distribution for \(\mu\)
\( \rho_\mu = \) location parameter for \(\lambda_u\) across the population; \(\lambda_u\) is \(\text{IG}(\rho_\mu,\tau_\mu)\)
\( \tau_\mu = \) scale parameter for \(\lambda_u\) across the population; \(\lambda_u\) is \(\text{IG}(\rho_\mu,\tau_\mu)\)
\( \{\kappa_{ui}\} = \) \((T \times 1)\) vector of expenditure sensitivity parameter for person \(i\)
\( \lambda_\kappa = \) \((h \times 1)\) vector of parameters for the exponential distribution of \(\kappa\)
\( \rho_\kappa = \) location parameter for \(\lambda_\kappa\) across the population; \(\lambda_\kappa\) is \(\text{IG}(\rho_\kappa,\tau_\kappa)\)
\( \tau_\kappa = \) scale parameter for \(\lambda_\kappa\) across the population; \(\lambda_\kappa\) is \(\text{IG}(\rho_\kappa,\tau_\kappa)\)

---

\(^4\)Gelfand and Smith(1990) introduced the notation "\([U|V]\)" for the conditional distribution (or density) of \(U\) given \(V\).
Also, define:

\[ n_i = (T \times 1 \text{ vector of choice data containing elements from N corresponding to person i}) \]

\[ q_i = (T \times 1 \text{ vector of quantity data containing elements from Q corresponding to person i}) \]

\[ X_i = (Tm \times k \text{ matrix of attributes containing elements from X corresponding to person i}) \]

\[ y_i = (Tm \times 1 \text{ vector of utilities attributes containing elements from Y corresponding to person i}) \]

\[ X^* = (Tmh \times k \text{ matrix obtained by stacking } X_i \text{ for all i}) \]

\[ y^* = (Tmh \times 1 \text{ vector obtained by stacking } y_i \text{ for all i}) \]

The following functional relationships exist in the hierarchical model:

(i) \([N, Q|Y, \{\mu_i\}, \{\kappa_i\}]\)

The choice decision \(n_i(j)\) and the quantity decision \(q_i(j)\) are related to the utility \(y_i(j)\) and model parameters \(\kappa_i\) and \(\mu_i\) through expressions for choice probability, \(Pr_{ni}(j)\) and purchase quantity probability, \(Pr_{ni}(q|j)\). Expressions for these probabilities appear in equations (49) and (65). The subscripts \(i\) and \(t\) were suppressed earlier for the sake of clarity.
(ii) \([Y|X, \alpha, \{\beta_i\}, \Sigma]\)

The utility per dollar, \(y_n(j)\), is a linear function of attributes \(x_n(j)\) of the alternatives and individual specific partworths \((\alpha+\beta_i)\). \(\alpha\) is the mean vector of partworths across the sample and \(\beta_i\) is vector of deviations from this mean for person \(i\).

\[
[y_n|X, \alpha, \beta_i, \Sigma] \sim N(X_i(\alpha + \beta_i), \Sigma)
\]  \hspace{1cm} (66)

(iii) \([\beta_i|D]\)

\(\beta_i\)'s are distributed normally across the population with a mean 0 and covariance matrix \(D\).

(iv) \([\{\mu_{ni}\}|\lambda_{\mu_i}]\)

The extreme value parameter \(\mu_{ni}\) (see eqn. 49) is unique for each person. Recall that \(1/\mu_{ni}\) is a measure of an individual’s price sensitivity. For every choice occasion, there exists a value \(\mu_{ni}\) which is consistent with person \(i\)'s purchase behavior. Across multiple choice occasions it is therefore reasonable to assume that \(\mu_{ni}\) follows a well defined distribution with some mean and variance. The parameters of this distribution are expected to be related to consumer choice and purchase quantity. In this dissertation I assume \(\mu_{ni}\) to follow an exponential distribution with mean \(\lambda_{\mu_i}\). Allowing \(\mu_{ni}\) to follow the exponential distribution has several advantages. First, it is now feasible to obtain draws from the full conditional distribution of \(\mu_{ni}\). Draws from the full conditional distributions from all model parameters are required to obtain estimates from the Gibbs sampler.
Second, the exponential distribution for \( \mu_i \) ensures that \( \mu_i \) is always non-negative. This is required since the scale parameter for the extreme value distribution is non-negative.

(v) \([\lambda_{\mu}|\rho_{\mu}, \tau_{\mu}]\)

The parameters \( \lambda_{\mu} \) across the sample are assumed to follow an IG(\( \rho_{\mu}, \tau_{\mu} \)) distribution. This distribution reflects the degree of heterogeneity in the sample with regard to the price sensitivity parameter. The choice of distribution for \( \lambda_{\mu} \) is influenced by the fact that it leads to a full conditional distribution which has well defined parametric form and is therefore easy to draw from. The first and second moments of the distribution IG(\( \rho_{\mu}, \tau_{\mu} \)) are informative about the average price sensitivity and the extent of price sensitivity dispersion across the sample.

(vi) \([\{\kappa_i\}|\lambda_{\kappa}]\)

The extreme value parameter \( \kappa_i \) (see eqn. 65) is unique for each person. Like \( \mu_i \), it is assumed to follow an exponential distribution with mean \( \lambda_{\kappa_i} \). Allowing \( \kappa_i \) to follow the exponential distribution also has advantages. First, it is now feasible to obtain draws from the full conditional distribution of \( \kappa_i \). Second, the exponential distribution for \( \kappa_i \) ensures that it is always non-negative. This is a reasonable a priori constraint since expenditure is expected to be non-negative.

(vii) \([\lambda_{\kappa}|\rho_{\kappa}, \tau_{\kappa}]\)

Similar to \( \lambda_{\mu} \), the parameters \( \lambda_{\kappa} \) across the sample are assumed to follow an IG(\( \rho_{\kappa}, \tau_{\kappa} \)) distribution. This distribution reflects the degree of heterogeneity in the sample with regard to the expenditure sensitivity parameter. The choice of distribution for \( \lambda_{\kappa} \) is
influenced by the fact that it leads to a full conditional distribution which has well defined parametric form and is therefore easy to draw from. The first and second moments of the distribution IG(p, τ) are informative about the average expenditure sensitivity and the extent of expenditure sensitivity dispersion across the sample.

Gibbs sampling is used to estimate the above hierarchical model. It requires that the draws from the full conditional distributions of the model parameters be available. Next, the expressions for full conditional distributions of the parameters to be estimated are developed. (Also see Gelfand and Smith 1990, Allenby and Lenk 1995 for details).

1. [α|X, {β_j}, Y, Σ]

Let

\[ y_{it}(j) = x_{it}(j) (α + β_j) - \ln p_{it}(j) + η_{it}(j) \tag{67} \]

where

\[ η \sim N(0, Σ) \]

Define \( y_{it}(j)^∗ \) as

\[ y_{it}(j)^∗ = y_{it}(j) - x_{it}(j) β_j + \ln p_{it}(j) = x_{it}(j) α + η_{it}(j) \tag{68} \]

If the prior distribution of [α] is N(0, A⁻¹), then the posterior conditional distribution is given by

\[ [α|X, {β_j}, Y, Σ] \sim N[\bar{α}, \Sigma_α] \tag{69} \]
where

\[ \Sigma_\alpha = [(X^*\Sigma^{-1}X^*) + A]^{-1} \]  

(70)

\[ \bar{\alpha} = \Sigma_\alpha X^*\Sigma^{-1}y^* \]  

(71)

Recall that \( y^* \) is the vector of \( y_{it(j)} \)'s across all i, t, j's and \( X^* \) is the matrix of \( x_{it(j)} \)'s across all i, t, j's.

2. \([\{\beta_i\} | Y, X, \alpha, \Sigma, D]\)

Define \( y_{it(j)}^{**} \) as

\[ y_{it(j)}^{**} = y_{it(j)} - x_{it(j)} \alpha + \ln p_{it(j)} = x_{it(j)} \beta_i + \eta_{it(j)} \]  

(72)

If \( \beta_i \sim N(0, D) \) is the prior on \( \beta_i \), then the posterior distribution of \( \beta_i \) is

\[ \beta_i \sim \text{MVN}(\bar{\beta}_i, \Sigma_{\beta_i}) \]  

(73)

where

\[ \bar{\beta}_i = \Sigma_{\beta_i} (X_i^*\Sigma^{-1}y_i^{**}) \]  

(74)

and

\[ \Sigma_{\beta_i} = [D^{-1} + X_i^*\Sigma^{-1}X_i]^{-1} \]  

(75)

\( y_i^{**} \) is a vector of \( y_{it(j)}^{**} \) for all t and j for person i.
3. \([D|{\beta_i}]\) 

The posterior distribution of \(D\) is given by

\[
[D|{\beta_i}] \sim IW\left(d_0+h, D_0+\Sigma_0\beta_0\beta_0'\right)
\]  \((76)\)

d_0 and \(D_0\) are the prior degrees of freedom and sum of squares for \(D\).

4. \([\Sigma|X,{\beta_i},\alpha,Y]\) 

In a brand situation

\[
\Sigma = S \otimes I_{t_r}; \text{\(S\) is a \((L \times L)\) diagonal matrix with elements } \sigma^2_l; \text{\(l=1,\ldots,L\)}
\]  \((77)\)

The posterior conditional distribution of \(\sigma^2_l\) is given by

\[
[\sigma^2_l|X, {\beta_i}, \alpha, Y] \sim IW(s_0 + hT, S_0 + e_i'e_i)
\]  \((78)\)

e_i'e_i is the sum of squares residuals from the regression equation involving those profiles which contain brand \(l\) only.

5. \([y_i|n_i,q_i,X_i,\beta_i,\alpha,D,\Sigma]\) 

It is known that

\[
y_{ii}(j) = (\alpha + \beta_i) x_{ii}(j) - \ln p_{ii}(j) + \eta_{ii}(j)
\]  \((79)\)

and

\[
\overline{y}_{ii}(j) = y_{ii}(j) + \epsilon_{ii}(j)
\]  \((80)\)
Also, we can write that

\[ [y_i | X_i, \alpha, \beta, \Sigma, n, q_j] \propto [n_i, q_j | y_i] [y_i | X_i, \alpha, \beta, \Sigma] \]  

(81)

Draws from the conditional distribution of \( y_{it}(j) \) can be obtained by using rejection sampling (Ripley 1987). Since \( Pr_{it}(j) \) is the probability that person \( i \) chooses brand \( j \) on purchase occasion \( t \) and \( Pr_{it}(q|j) \) is the probability that a quantity \( q \) is bought for the chosen brand \( j \), the joint probability of choosing alternative \( j \) and quantity \( q \), \( Pr_{it}(q,j) \) is

\[ Pr_{it}(q,j) = Pr_{it}(j) \cdot Pr_{it}(q|j) \]  

(82)

where

\[ Pr_{it}(j) = \frac{\exp (y_{it}(j)/\mu_{it})}{\sum_k \exp (y_{it}(k)/\mu_{it})} \]  

(83)

and

\[ Pr_{it}(q|j) = F_y^- (0.5 \cdot p_{it}(j) \kappa_{it}) \text{ for } q_{it}(j) = 0 \]
\[ = F_y^- ((q_{it}(j) + 0.5) \cdot p_{it}(j) \kappa_{it}) - F_y^- ((q_{it}(j) - 0.5) \cdot p_{it}(j) \kappa_{it}) \text{ for } q_{it}(j) > 0 \]  

(84)
This is easy to evaluate. If person \( i \) chooses the \( j \)th alternative, then as established in equation (59) before,

\[
\bar{y}_{it}(j) \sim EV(\theta', \xi') \text{ where,} \\
\theta' = \mu_{it}', \\
\xi' = \mu_{it}' \ln (Pr_{it}(j))^{-1} + y_{it}(j) \\
F_{\xi'}(k) = \exp (-\exp(\frac{\xi'-k}{\theta'}))
\]  

(85)

The rejection sampling will therefore involve the following two step process:

(i) Draw \( y_{it}(j) \) for brand \( k \) from \( N((\alpha+\beta_i) x_{it}(j) - \ln p_{it}(j), \sigma_{it}^2) \)

(ii) Accept a draw with rejection sampling probability \( Pr_{it}(q_{ij}) \).

6. \([\lambda_{\mu|i}, \{\mu_{it}\}, \tau_{\mu}, \rho_{\mu}]\)

For person \( i \) and choice occasion \( t \),

\[
\mu_{it} \sim \exp (\lambda_{\mu|i}) \ ; \ \mu_{it} > c_m, \text{ a constant}
\]  

(86)

c_m can be chosen to define an reasonable range for the extreme value scale parameter.

\[
f(\mu_{it}) = \frac{1}{\lambda_{\mu|i}} \exp \left(-\frac{(\mu_{it} - c_m)}{\lambda_{\mu|i}}\right), \ t = 1, ..., T
\]  

(87)

the likelihood function of \( \lambda_{\mu|i} \) is given by

\[
\mathcal{L}(\lambda_{\mu|i}) = \prod_t \frac{1}{\lambda_{\mu|i}} \exp \left(-\frac{(\mu_{it} - c_m)}{\lambda_{\mu|i}}\right)
\]  

(88)
Across people, let $\lambda_{\mu i}$ be distributed Inverse Gamma $(\rho_{\mu i}, \tau_{\mu})$ with the pdf

$$g(\lambda_{\mu i}) = \frac{1}{\Gamma_{\rho_{\mu i}} \tau_{\mu}^{\rho_{\mu i}} \lambda_{\mu i}^{\rho_{\mu i} - 1}} \exp \left( - \frac{1}{\tau_{\mu} \lambda_{\mu i}} \right)$$

(89)

From equations (88) and (89), the posterior conditional distribution of $\lambda_{\mu i}$ is

$$\pi[\lambda_{\mu i} | \mu_{\mu i}, \tau_{\mu}, \rho_{\mu}] \propto \left( \prod_{i} \frac{1}{\lambda_{\mu i}} \exp \left( - \frac{\mu_{\mu i} - c_{m}}{\lambda_{\mu i}} \right) \frac{1}{\Gamma_{\rho_{\mu i}} \tau_{\mu}^{\rho_{\mu i}} \lambda_{\mu i}^{\rho_{\mu i} - 1}} \exp \left( - \frac{1}{\tau_{\mu} \lambda_{\mu i}} \right) \right)$$

$$\propto \frac{1}{\lambda_{\mu i}^{\rho_{\mu i} + 1}} \exp \left( - \frac{1}{\lambda_{\mu i}} \left[ \frac{1}{\tau_{\mu}} + \sum_{i} (\mu_{\mu i} - c_{m}) \right] \right)$$

(90)

$$\sim IG \left( (\rho_{\mu} + T), \left[ \frac{1}{\tau_{\mu}} + \sum_{i} (\mu_{\mu i} - c_{m}) \right]^{-1} \right)$$

where $T$ is the number of choice occasions for the respondent.

7. $[\tau_{\mu} | \lambda_{\mu i}, \rho_{\mu}]$

The prior distribution of $\tau_{\mu}$ is

$$[\tau_{\mu}] \sim IG \left( \rho_{0}, \tau_{0} \right)$$

(91)

The likelihood function is

$$\mathcal{L}(\tau_{\mu}) = \prod_{i} \frac{1}{\Gamma_{\rho_{\mu i}} \tau_{\mu}^{\rho_{\mu i}} \lambda_{\mu i}^{\rho_{\mu i} - 1}} \exp \left( - \frac{1}{\tau_{\mu} \lambda_{\mu i}} \right)$$

$$\propto \frac{1}{\tau_{\mu}^{\rho_{\mu} h}} \exp \left( - \frac{1}{\tau_{\mu}} \sum_{i} \frac{1}{\lambda_{\mu i}} \right)$$

(92)

where $h$ is the number of respondents. The posterior conditional distribution of $\tau_{\mu}$ is
\[
\pi(\tau_\mu | \lambda_\mu, \rho_\mu) \propto \frac{1}{\tau_\mu^{\rho_{\mu}^{-1}}} \exp\left(-\frac{1}{\tau_\mu} \sum_i \frac{1}{\lambda_{\mu i}}\right) \frac{1}{\Gamma_{\rho_0} \tau_0^{\rho_0^{-1}}} \exp\left(-\frac{1}{\tau_0 \tau_\mu}\right)
\]

\[
= \frac{1}{\tau_\mu^{\rho_{\mu}^{-1}}} \exp\left(-\frac{1}{\tau_\mu} \left[\sum_i \frac{1}{\lambda_{\mu i}^{-1}}\right]\right)
\] (93)

\[
\sim IG(\rho_\mu h + \rho_0, \left[\frac{1}{\tau_0} + \sum_i \frac{1}{\lambda_{\mu i}^{-1}}\right])
\]

8. \([\rho_\mu | \lambda_\mu, \tau_\mu]\)

The posterior distribution of \(\rho_\mu\) is obtained as follows. This approach is suggested by Jen (1995).

**Prior distribution of \(\rho_\mu, \pi(\rho_\mu) \sim \text{Discrete uniform } N_0\)**

\[
L(\rho_\mu) = \prod_i \frac{1}{\Gamma_{\rho_\mu} \tau_\mu^{\rho_{\mu}^{-1}} \lambda_{\mu i}^{\rho_{\mu}^{-1}}} \exp\left(-\frac{1}{\tau_\mu \lambda_{\mu i}}\right)
\]

**Posterior distribution** \(\pi(\rho_\mu | \lambda_\mu, \tau_\mu) \propto \prod_i \frac{\left(1/\tau_\mu \lambda_{\mu i}\right)^{\rho_{\mu}^{-1}}}{\Gamma_{\rho_\mu}} \exp\left(-\frac{1}{\tau_\mu \lambda_{\mu i}}\right)
\]

\[
\propto \prod_i \frac{\left(1/\tau_\mu \lambda_{\mu i}\right)^{\rho_{\mu}^{-1}}}{(\rho_\mu - 1)!} \exp\left(-\frac{1}{\tau_\mu \lambda_{\mu i}}\right)
\]

\[
= \prod_i f(\rho_\mu = \rho_{\mu} - 1, \left[\frac{1}{\tau_\mu \lambda_{\mu i}}\right])
\]

where \(f(.)\) is the pdf for the poisson distribution with the mean \(\frac{1}{\tau_\mu \lambda_{\mu i}}\).

9. \([\{\mu_\mu\} | \lambda_\mu, n, q, \mu]\)

\[
[\{\mu_\mu\} | \lambda_\mu, n, q, \mu] \propto [n, q | \{\mu_\mu\}][\{\mu_\mu\} | \lambda_\mu]
\] (95)
Draws for $\mu_{it}$ can be obtained by using rejection sampling. The following steps need to be followed:

(i) Draw $\mu_{it}$ from $\exp(\lambda_{it})$, $\mu_{it} > c_k$

(ii) Accept this draw with rejection probability $\Pr_{it}(q_{ij})$. $\Pr(q_{ij})$ is obtained as before (equations 83 and 84).

10. $[\lambda_{xi}, \{\kappa_i\}, \tau_x, \rho_x]$  

For person $i$, choice occasion $t$,

$$
\kappa_{it} \sim \exp(\lambda_{xt}); \quad \mu_{it} > c_k, \text{ a constant} 
$$

$c_k$ can be chosen to define an acceptable range for the expenditure sensitivity parameter. or

$$
f(\kappa_t) = \frac{1}{\lambda_{xt}} \exp \left( - \frac{\kappa_t - c_k}{\lambda_{xt}} \right), \quad t = 1, ..., T 
$$

The likelihood function of $\lambda_{xi}$ is

$$
\mathcal{L}(\lambda_{xi}) = \prod_t \frac{1}{\lambda_{xt}} \exp \left( - \frac{\kappa_{it} - c_k}{\lambda_{xi}} \right) 
$$

Across people, let $\lambda_{xi}$ be distributed inverse Gamma $($$\rho_x, \tau_x$$)$ with the pdf

$$
g(\lambda_{xi}) = \frac{1}{\Gamma(\rho_x)} \frac{\tau_x^{\rho_x}}{\lambda_x^{\rho_x + 1}} \exp \left( - \frac{1}{\tau_x \lambda_{xi}} \right) 
$$
Then the posterior conditional distribution of $\lambda_{ki}$ is

$$
\pi(\lambda_{ki} | \{ \kappa_{it} \}) \propto \left( \prod_i \frac{1}{\lambda_{ki}} \exp \left( - \frac{\kappa_{it} - c_k}{\lambda_{ki}} \right) \right) \frac{1}{\Gamma_p \tau_k \lambda_{ki}^{\rho_p + 1}} \exp \left( - \frac{1}{\tau_k \lambda_{ki}} \right)
$$

$$
\propto \frac{1}{\lambda_{ki}^{\rho_p + r + 1}} \exp \left( - \frac{1}{\lambda_{ki}} \left[ \frac{1}{\tau_k} + \sum_i (\kappa_{it} - c_k) \right] \right) \tag{100}
$$

$$
\sim IG \left( (\rho_k + T, \left[ \frac{1}{\tau_k} + \sum_i (\kappa_{it} - c_k) \right]^{-1} \right)
$$

where $T$ is the number of choice occasions for the respondent.

11. $[\tau_k | \lambda_{ki}, \rho_k]$

The prior distribution of $\tau_k$ is

$$
[\tau_k] \sim IG \left( \rho_1, \tau_1 \right) \tag{101}
$$

The likelihood function is

$$
\mathcal{L}(\tau_k) = \prod_i \frac{1}{\Gamma_p \tau_k \lambda_{ki}^{\rho_p + 1}} \exp \left( - \frac{1}{\tau_k \lambda_{ki}} \right)
$$

$$
\propto \frac{1}{\tau_k^{\rho_p + r + 1}} \exp \left( - \frac{1}{\tau_k} \sum_i \frac{1}{\lambda_{ki}} \right) \tag{102}
$$

where $h$ is the number of respondents. The posterior conditional distribution of $\tau_k$ is

$$
\pi(\tau_k | \lambda_k) \propto \frac{1}{\tau_k^{\rho_p + r + 1}} \exp \left( - \frac{1}{\tau_k} \sum_i \frac{1}{\lambda_{ki}} \right) \frac{1}{\Gamma_p \tau_1 \tau_k^{\rho_1 + 1}} \exp \left( - \frac{1}{\tau_1 \tau_k} \right)
$$

$$
\propto \frac{1}{\tau_k^{\rho_p + r + 1}} \exp \left( - \frac{1}{\tau_k} \left[ \sum_i \frac{1}{\lambda_{ki}} + \frac{1}{\tau_1} \right] \right) \tag{103}
$$

$$
\sim IG \left( \rho_k h + \rho_1, \left[ \frac{1}{\tau_1} + \sum_i \frac{1}{\lambda_{ki}} \right]^{-1} \right)
$$
12. $[\rho_{k}|\lambda_{k},\tau_{k}]$

*Prior distribution of $\rho_{k}$, $\pi(\rho_{k}) \sim$ Discrete uniform $N_1$*

\[
\mathcal{L}(\rho_{k}) = \prod_{i} \frac{1}{\Gamma_{\rho_{k}} \tau_{k}^{\rho_{k}} \lambda_{ki}^{\rho_{k}+1}} \exp(-\frac{1}{\tau_{k} \lambda_{ki}})
\]

*Posterior distribution $\pi(\rho_{k}|\lambda_{k},\tau_{k}) \propto \prod_{i} \frac{(1/\tau_{k} \lambda_{ki})^{\rho_{k}-1}}{\Gamma_{\rho_{k}}} \exp(-\frac{1}{\tau_{k} \lambda_{ki}})\]

\[
\propto \prod_{i} \frac{(1/\tau_{k} \lambda_{ki})^{\rho_{k}-1}}{(\rho_{k} - 1)!} \exp(-\frac{1}{\tau_{k} \lambda_{ki}})
\]

\[
\propto \prod_{i} f(\rho_{k} = \rho_{k} - 1|\tau_{k} \lambda_{ki})
\]

where $f(.)$ is the pdf for the Poisson distribution with the mean $\frac{1}{\tau_{k} \lambda_{ki}}$.

13. $[\{k_{it}\}|\lambda_{ki},n_{i},q_{i}]$

\[
[\{k_{it}\}|\lambda_{ki},n_{i},q_{i}] \propto [n_{i},q_{i}|\{k_{it}\}][\{k_{it}\}|\lambda_{ki}]
\] (105)

Draws for $k_{it}$ can be obtained by using rejection sampling. The following steps need to be followed: (i) Draw $k_{it}$ from $\exp(\lambda_{ki})$, $k_{it}>c_{k}$.

(ii) Accept this draw with rejection probability $Pr_{it}(q_{i})$ (equations 83 and 84).

The thirteen (13) full conditional distributions described above are used by the Gibbs sampler to obtain estimates of the model parameters. A draw from each conditional distribution described above is generated in sequence. The draw from the previous full conditional distribution is used to update the parameters of the current full conditional distribution. If this process is repeated enough number of times then, upon
convergence, it leads to stationary posterior distribution for the parameters. Draws from the stationary posterior distribution of each parameter allow for the empirical calculation of the mean and standard deviation of the parameter.

To summarize this chapter, in part 1 I gave an introduction of the translog utility function. In part 2, this specification of the utility function is used to develop the demand equation for the model (equation 57). A hierarchical Bayes model which captures the functional relationships involving choice probability (equation 49) and quantity (equation 65) developed in part 2 is presented in part 3. Finally, expressions for full conditional distributions for the parameters involved in the model are presented. Next, I use data collected through a field study to calibrate, validate and test the model developed in this chapter.
CHAPTER IV

Empirical Application

The objectives of the empirical analysis reported in this chapter are to (i) estimate the parameters of the model proposed in chapter III, (ii) demonstrate how the model can be used to study primary demand and (iii) test the predictive ability of the model. The chapter is divided into two parts. Part 1 describes the data used in the research. Results are presented in Part 2. Managerial implications of findings reported in this chapter are discussed in the next chapter.

1. Data Description

Data were obtained with the help of Marketing Information Systems International (MISI) Inc., Englewood Cliffs, New Jersey. The proposed model was built based upon discussions with representatives from MISI. The involvement of MISI in this research was helpful in two important ways. First, it helped in the model development stage by bringing in an applied perspective to the research problem being investigated. This was instrumental in this research being relevant from a brand manager’s perspective. Second, it provided the data to test the model. This was helpful in calibrating and validating the model.
The product used for this study was canned vegetable soup. The product choice was influenced by two factors. First, vegetable soup consumption for a given individual (family) was expected to be related to product attributes such as ease of usage and calories. Recall that the proposed model attempts to establish the link between product attributes and quantity. Second, it was expected that the vegetable soup consumption across individuals would vary. Since product quantity is one of the dependent variables in the model, a large variation in vegetable soup consumption across the sample could potentially provide useful insights into the differential impact of product design changes on individual level purchase quantity.

The study was conducted through intercept interviews in shopping malls in a city in northern New Jersey. Data were collected between the periods of 12 and 9 pm and covered every day of the week except Sunday. An age quota of 20 respondents per age group (see Appendix A, Question 1a) was imposed in order to capture respondents from all age groups. A total of 185 completed responses were obtained for the study.

Product attributes and levels for the study were selected based upon information collected from Consumer Reports (1993). Five product attributes were chosen (Table 2). Two discrete levels were selected for four of the five attributes. The fifth attribute, price, was allowed to be a continuous variable. The price range chosen was between $1.20 and $3.60. Price for each profile was allowed to be correlated with the design features of the product. The design for the conjoint study was developed as follows.

Based upon the four discrete attributes, an orthogonal design comprised of eight (8) profiles was obtained. Pairs of profiles for the conjoint task were obtained by
matching each one of these eight profiles with their complements. For example, a profile with the following product description: Progresso, Light (60 calories), condensed and 800 mg salt was matched by the product description: Campbell, Hearty (120 calories), ready to serve and 200 mg salt. This resulted in pairs of profiles with non-similar levels for each attribute (Pair numbers 1, 2, 4, 5, 7, 8, 10 and 11 in Appendix B).

Product price was allowed to be correlated to the product description. In order to get a wide dispersion of the price range across profiles, the following guidelines were followed. First, it was assumed that all else equal, Campbell is preferred over Progresso, a hearty 120 calories soup is preferred over a thin broth 60 calories soup, a ready to serve soup is preferred over condensed soup and a soup with 200 mg. salt is preferred over a soup with 800 mg. salt. Further, it was assumed that a price differential of $0.50 exists between the levels for all four attributes. The preferred attribute level being more expensive. The price for each product profile was then determined by the number of preferred attribute levels in that profile. A random error is added to the price corresponding the profile so that the price is not perfectly correlated with rest of the attributes. Consider, for example, the first paired comparison in Appendix B. Note that all four attributes in the profile on the right hand side are the preferred attribute levels. The price differential between the two profiles should therefore be $2.00 (i.e. 4 times $0.50) plus a random error of -$0.20.
Table 2  
Vegetable Soup Attributes

<table>
<thead>
<tr>
<th>Number</th>
<th>Attribute Description</th>
<th>Attribute Levels/Range</th>
<th>Dummy Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Brand name</td>
<td>Campbell, Progresso</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Calorie content per 8 oz. serving</td>
<td>120 calories, 60 calories</td>
<td>1, 0</td>
</tr>
<tr>
<td>3</td>
<td>Ease of usage</td>
<td>Ready to serve, Condensed</td>
<td>1, 0</td>
</tr>
<tr>
<td>4</td>
<td>Salt content per 8 oz. serving</td>
<td>200mg, 800mg</td>
<td>1, 0</td>
</tr>
<tr>
<td>5</td>
<td>Price for four 8 oz. servings</td>
<td>$1.20 to $3.60</td>
<td>-</td>
</tr>
</tbody>
</table>

Four more pairs of profiles were added to the design with the purpose of obtaining quantity data for product profiles with unattractive features such as high price, high salt, low convenience or a combination thereof (Pair numbers 3, 6, 9 and 12 in Appendix B). These four profile pairs were a subset the eight pairs described earlier with the following modifications. Pair number 3 had both profiles with high salt. Pair number 6 had both profiles with a high price. Pair number 9 had both profiles with a high price and high salt. Finally, pair number 12 had both profiles with the condensed soup option. Purchase/non-purchase and quantity data for these four unattractive product profiles was expected to be informative about reservation value for each respondent.
In all, each respondent was shown 12 paired comparisons. Every respondent saw the same 12 paired comparisons. The order in which the pairs were presented to the respondents was randomized across individuals. Also, the order in which the attributes were presented within a profile was varied across paired comparisons. These steps were taken to rule out any order effects.

Each respondent was asked a series of questions as listed in the questionnaire in Appendix A. Only those respondents were included in the sample who ate dinner at home. The survey began with questions about the respondent's age and gender. This was followed by a conjoint task. In this task, first a description of product attributes and their levels was read to the respondents. This was followed by asking the respondents to select a product profile from a pair of profiles. This was done by presenting the respondent with a pair of cards with product descriptions printed on them (Appendix B). Twelve paired comparisons were shown to each respondents.

After finishing the conjoint task, each respondent was asked quantity related information. The twelve preferred product profiles from the conjoint task were used to get this information. For each one of these twelve profiles, the respondent was asked to indicate the number of times in an average 4-week period in the winter that their household would consume such a product.

After obtaining preference and quantity data, the respondents were asked a series of questions on their behaviors, attitudes and demographics. Behavior related questions included whether they buy vegetable soups for their household, which vegetable soup brands do they buy, how often do they have vegetables with dinner, how often they have
dinner with their family, whether they read product labels and how busy they are.

Questions on attitudes covered variables such as health consciousness and importance of convenience. Demographic information was obtained through questions on family size, education, marital status, number of work-hours per week for self, number of work-hours per week for spouse, income, sex and age. This information was used in the analysis to develop a demographic/attitudinal/behavioral profile of segments in the market.

2. Results

Gibbs sampling was used to obtain the parameter estimates. As seen in figure 1, draws from the posterior distribution of the four partworths appear to reach a stationary distribution very quickly. This is evident from the fact that the series of draws for each partworth have a constant mean and variance. Visual inspection of the draws in figure 1, therefore, indicates that the posterior distributions of the four partworths have converged to stationarity. Upon convergence, draws from the distributions were used to evaluate the mean and standard deviations of the parameter estimates. The Gibbs sampler ran for 2000 iterations and the last 1000 iterations were used to obtain parameter estimates.
The results are divided into four sub-parts. These are: Parameter estimates, Primary demand analysis, Predictive test and Sensitivity Analysis.

(i) Parameter estimates:

Table 3 reports the estimates of the fixed effect of the partworths across the sample. The fixed effects estimates may be interpreted as the mean of the partworths across the sample. As seen from the table, on an average, Campbell is slightly more preferred than Progresso. Also, this sample tends to prefer a soup which is hearty, contains lots of vegetables and has 120 calories per 8 oz. serving to one that is light, is based on a relatively thinner broth and has 60 calories per 8 oz. serving\(^5\). Ready to serve vegetable soups which require minimal cooking effort have a higher preference over condensed soups which require some cooking effort. Also, an 8 oz. vegetable soup serving with 200 mg. of sodium is preferred over an identical serving with 800 mg. of sodium. Fixed effect partworth estimates reported in table 3 are statistically significant at 0.05. Recall that the partworth for one level for each of the four attributes was set to zero (Table 2). A statistically significant estimate therefore implies that the four partworth estimates are non-zero. In other words, across the sample, the two levels chosen for each of the four attributes are not equally valued by the respondents.

\(^5\)The respondents were given the description of attributes and levels prior to beginning the conjoint task. See first page of the questionnaire in Appendix A.
Table 3  
Fixed Effect Partworths\textsuperscript{a}  
(Posterior Standard Deviation)

<table>
<thead>
<tr>
<th></th>
<th>Brand name</th>
<th>Calorie content</th>
<th>Ease of usage</th>
<th>Salt content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partworth</td>
<td>0.158</td>
<td>0.173</td>
<td>0.302</td>
<td>1.101</td>
</tr>
<tr>
<td>Estimate</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(.08)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}: Estimates are significant at $\alpha=0.05$.

A key finding in table 3 is that on an average, salt content dominates other product attributes in terms of importance. The second most important product attribute is ease of usage. The other two attributes namely brand name and calorie content are relatively less important\textsuperscript{6}.

The matrix of covariation in table 4 indicates the extent of heterogeneity and patterns of correlation in the partworths across the sample. Although all four diagonal elements are statistically significant, none of the correlations reported in table 4 are significant. Therefore, across the sample there appears to be no systematic pattern of correlation between attribute importance for the four attributes. Only the diagonal elements of table 4 are interpretable. The diagonal elements indicate that for the chosen sample, the largest variation in partworths occurs for the brand name attribute. The least amount of variation occurs for the ease of usage attribute.

\textsuperscript{6}Conclusions regarding relative importance of attributes are conditional on the attribute levels chosen for the study.
Table 4
Matrix of Covariation (D)*
(Posterior Standard Deviation)

<table>
<thead>
<tr>
<th></th>
<th>Brand name</th>
<th>Calorie content</th>
<th>Ease of usage</th>
<th>Salt content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand name</td>
<td>1.20</td>
<td>-0.04</td>
<td>0.00</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.09)</td>
<td>(0.12)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Calorie content</td>
<td>-0.04</td>
<td>0.73</td>
<td>0.18</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.12)</td>
<td>(0.13)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Ease of usage</td>
<td>0.00</td>
<td>0.10</td>
<td>0.44</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Salt content</td>
<td>-0.10</td>
<td>-0.11</td>
<td>-0.04</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.15)</td>
</tr>
</tbody>
</table>

* Correlations are reported in the upper right portion of the table.

A unique feature of the proposed model is that it allows individual level inference. Table 5 reports parameter estimates for five respondents from the study. From the table, it is seen that 47% of the parameters are significant. For these five respondents, the salt content partworth, mean of the extreme value distribution and mean of the expenditure sensitivity estimates are statistically significant the most number of times. Among the four non-price attributes, salt content is the most important attribute for all five respondents.

The mean of the extreme value distribution ($\lambda_{\mu}$) is a measure of an individual’s price sensitivity. Higher the value of $\lambda_{\mu}$, lower is the price sensitivity. Table 5 indicates that respondents 20, 40, 60 and 80 are almost equally price sensitive. Respondent
<table>
<thead>
<tr>
<th>Profile/Parameters</th>
<th>Respondent Number</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>100</td>
</tr>
<tr>
<td>Brand name partworth</td>
<td>0.74 (0.49)</td>
</tr>
<tr>
<td></td>
<td>0.05 (0.56)</td>
</tr>
<tr>
<td></td>
<td>-0.33 (0.51)</td>
</tr>
<tr>
<td></td>
<td>0.73 (0.44)</td>
</tr>
<tr>
<td></td>
<td>0.03 (0.60)</td>
</tr>
<tr>
<td>Calories partworth</td>
<td>-0.33 (0.49)</td>
</tr>
<tr>
<td></td>
<td>-0.08 (0.50)</td>
</tr>
<tr>
<td></td>
<td>-0.44 (0.47)</td>
</tr>
<tr>
<td></td>
<td>-1.27* (0.49)</td>
</tr>
<tr>
<td></td>
<td>-0.02 (0.54)</td>
</tr>
<tr>
<td>Ease of usage partworth</td>
<td>0.60 (0.49)</td>
</tr>
<tr>
<td></td>
<td>-0.28 (0.45)</td>
</tr>
<tr>
<td></td>
<td>-0.07 (0.64)</td>
</tr>
<tr>
<td></td>
<td>-0.13 (0.43)</td>
</tr>
<tr>
<td></td>
<td>0.17 (0.47)</td>
</tr>
<tr>
<td>Salt content partworth</td>
<td>1.90* (0.49)</td>
</tr>
<tr>
<td></td>
<td>1.48* (0.74)</td>
</tr>
<tr>
<td></td>
<td>1.56* (0.64)</td>
</tr>
<tr>
<td></td>
<td>1.39* (0.49)</td>
</tr>
<tr>
<td></td>
<td>1.62* (0.51)</td>
</tr>
<tr>
<td>Mean of EV distribution</td>
<td>0.26 (0.16)</td>
</tr>
<tr>
<td>((\lambda_{ev}))</td>
<td>0.25 (0.15)</td>
</tr>
<tr>
<td></td>
<td>0.24 (0.14)</td>
</tr>
<tr>
<td></td>
<td>0.29 (0.16)</td>
</tr>
<tr>
<td></td>
<td>0.55* (0.35)</td>
</tr>
<tr>
<td>Mean of Expenditure</td>
<td>0.69 (0.30)</td>
</tr>
<tr>
<td>insensitivity ((\lambda_{n}))</td>
<td>3.59 (4.11)</td>
</tr>
<tr>
<td></td>
<td>4.26 (8.01)</td>
</tr>
<tr>
<td></td>
<td>0.35* (0.22)</td>
</tr>
<tr>
<td></td>
<td>0.15* (0.07)</td>
</tr>
<tr>
<td>Buy vegetable soup</td>
<td>Yes</td>
</tr>
<tr>
<td>Eat dinner at home</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Convenience is important</td>
<td>Yes</td>
</tr>
<tr>
<td>Eat vegetables with dinner</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Number of family members</td>
<td>2</td>
</tr>
<tr>
<td>Age in years</td>
<td>41-50</td>
</tr>
<tr>
<td>Work hours per week</td>
<td>40</td>
</tr>
</tbody>
</table>

*: Significant at \(\alpha=0.1\)

Number 100 on the other hand is less price sensitive than the others. Similarly, \(\lambda_{n}\) is a measure of an individual's expenditure insensitivity. This measure indicates the sensitivity of a family's expenditure on vegetable soup to the utility per dollar that the product offers. Higher the value of \(\lambda_{n}\), lower is the expenditure sensitivity. From the table it is seen that respondent number 100 is the most expenditure sensitive. Respondent
numbers 40 and 60 have a non-significant expenditure insensitivity parameter. The large estimates of expenditure insensitivity for these two individuals are however consistent with their buying behavior because both these respondents do not buy vegetable soup. The relationship between parameter estimates and demographic, attitudinal and behavioral variables is investigated for the entire sample later.

Figure 2 demonstrates the extent of variability in model parameters across the sample. Based upon how the dummy variables for partworths are set up (Table 2), the partworths should be interpreted as follows. A positive partworth for brand name implies that Campbell is preferred over Progresso, all else equal. Similarly, a positive partworth for calories implies that a hearty, 120 calories/8 oz. serving soup is preferred over a thin broth, 60 calories/8 oz. serving soup, all else equal. A positive partworth for ease of usage partworth implies that a ready-to-serve soup is preferred over a condensed soup, all else equal. A positive partworth for salt content partworth implies that a soup with 200 mg. salt/8 oz. serving is preferred over a soup with 800 mg salt/8 oz. serving, all else equal.

It was seen earlier in table 4 that on an average, the sample prefers Campbell over Progresso, high calories over low calories, ready-to-serve over condensed and low salt over high salt. Figure 2, however, is more informative as it reflects individual level preferences. As an example, for the brand name partworth, it can be seen that there are more people with a positive partworth than with a negative partworth. This implies that there are more people who prefer Campbell over Progresso than those who prefer Progresso over Campbell. However, there exits a sizable group of individuals who prefer
Progresso over Campbell. Similarly there is a group of people who prefer the thin broth, 60 calories/8 oz. serving soup over the hearty, 120 calories/8 oz serving soup. These are the individuals with a negative partworth for the calories partworth. Also there is a group of people who prefer the condensed vegetable soup over the ready-to-serve soup. These are the individuals with a negative partworth for the ease of usage partworth. Finally, there is a group of people who prefer a soup with 800 mg. salt/8 oz. serving over a soup with 200 mg. salt/8 oz. serving. These are the individuals with a negative partworth for the salt content partworth. The distributions of partworths in figure 2 are therefore informative about the diversity in consumer preferences across the sample.

From a brand manager's perspective, it is useful to identify groups of individuals with needs that are different from rest of the population. This can suggest ideas for new product designs in order to satisfy the unique needs of a market segment. The issue of heterogeneity of consumer preferences will be explored further in primary demand analysis reported later.

The other two parameters displayed in figure 2 are the scale parameter of the extreme value distribution and the expenditure sensitivity parameter. As explained in the previous chapter, the extreme value parameter is a measure of price sensitivity. For both these parameters, higher the value of the parameter, lower the sensitivity. The purpose of displaying the distributions of these two parameters in figure 2 is to demonstrate that there is a variability in price sensitivity and expenditure sensitivity across the sample. The effect of this variability in parameters has substantive implications for a brand manager as is shown in the primary demand analysis part of this chapter.
FIGURE 2
DISTRIBUTION OF HETEROGENEITY FOR MODEL PARAMETERS
As stated earlier, information on heterogeneity among respondents is useful in identifying groups of individuals with similar needs. Next, I investigate if there are any systematic differences in these model parameters by demographic, attitudinal and behavioral variables.

Table 6
Differences in Model Parameters by Demographic/Attitudinal Variables

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Description of Differences</th>
<th>Difference in Parameter (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>Younger people (&lt;50 years) are more convenience sensitive than older people</td>
<td>0.26(0.08)</td>
</tr>
<tr>
<td></td>
<td>Younger people (&lt;50 years) are more expenditure sensitive than older people</td>
<td>0.61(0.36)</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td>Males prefer Progresso more than females</td>
<td>0.33(0.19)</td>
</tr>
<tr>
<td><strong>Eat dinner at home</strong></td>
<td>People who eat dinner at home all the time are more expenditure sensitive</td>
<td>0.90(0.16)</td>
</tr>
<tr>
<td></td>
<td>People who eat dinner at home all the time are less price sensitive</td>
<td>0.25(0.13)</td>
</tr>
<tr>
<td><strong>Brand bought</strong></td>
<td>Campbell buyers have a higher preference for Campbell than Progresso buyers</td>
<td>0.49(0.18)</td>
</tr>
<tr>
<td><strong>Health</strong></td>
<td>Health Conscious people are more salt content sensitive</td>
<td>0.47(0.17)</td>
</tr>
<tr>
<td><strong>Read labels</strong></td>
<td>People who read labels are more salt sensitive</td>
<td>0.46(0.18)</td>
</tr>
<tr>
<td></td>
<td>People who read labels are more expenditure sensitive</td>
<td>0.96(0.41)</td>
</tr>
<tr>
<td><strong>Convenience orientation</strong></td>
<td>Convenience oriented people like ready to serve soups more</td>
<td>0.26(0.09)</td>
</tr>
<tr>
<td></td>
<td>Convenience oriented people are less price sensitive</td>
<td>0.28(0.13)</td>
</tr>
<tr>
<td></td>
<td>Convenience oriented people are more expenditure sensitive</td>
<td>1.22(0.37)</td>
</tr>
<tr>
<td><strong>Busy</strong></td>
<td>Busy people prefer Campbell</td>
<td>0.44(0.19)</td>
</tr>
<tr>
<td></td>
<td>Busy people are less calorie conscious</td>
<td>0.23(0.13)</td>
</tr>
<tr>
<td></td>
<td>Busy People are more convenience oriented</td>
<td>0.22(0.09)</td>
</tr>
<tr>
<td></td>
<td>Busy people are more expenditure sensitive</td>
<td>0.74(0.38)</td>
</tr>
<tr>
<td><strong>Try new products</strong></td>
<td>People who try new products prefer Campbell</td>
<td>0.43(0.22)</td>
</tr>
<tr>
<td></td>
<td>People who try new products are less calorie conscious</td>
<td>0.20(0.12)</td>
</tr>
<tr>
<td></td>
<td>People who try new products like convenience more</td>
<td>0.24(0.09)</td>
</tr>
<tr>
<td></td>
<td>People who try new products are less price sensitive</td>
<td>0.24(0.15)</td>
</tr>
<tr>
<td></td>
<td>People who try new products are more expenditure sensitive</td>
<td>1.50(0.35)</td>
</tr>
<tr>
<td><strong>Family size</strong></td>
<td>Big families are less calorie conscious</td>
<td>0.35(0.12)</td>
</tr>
<tr>
<td></td>
<td>Big families are more convenience oriented</td>
<td>0.17(0.08)</td>
</tr>
<tr>
<td><strong>Income</strong></td>
<td>People with over $50,000 family income prefer Progresso more</td>
<td>0.52(0.21)</td>
</tr>
<tr>
<td></td>
<td>People with over $50,000 family income are less price sensitive</td>
<td>0.40(0.14)</td>
</tr>
<tr>
<td></td>
<td>People with over $50,000 family income are less expenditure sensitive</td>
<td>1.12(0.39)</td>
</tr>
</tbody>
</table>

*: Only statistically significant (α=0.1) differences are reported.
Table 6 reports differences in model parameters by demographic, attitudinal and behavioral variables. The purpose of this analysis was to conduct an exploratory investigation of whether there is a relationship between model parameters and respondent demographics, attitudes and behaviors. It was found that there is a statistically significant relationship between a number of model parameters and descriptor variables such as demographics, attitudes and behaviors. Since this was a preliminary investigation of the model parameters, the sample was divided into two groups, one variable at a time. For example, I divided the sample into younger (less than or equal to 50 years of age) and older (greater than 50 years of age). Next I looked for differences between the two groups with regard to the six model parameters namely the four partworths, the price sensitivity parameter and the expenditure sensitivity parameter. Groups were formed based upon respondent specific information such as age, sex, health consciousness, and convenience orientation collected at the time of the survey. A description of the groups formed, their differences and the magnitude of the difference appears in table 6. Only the statistically significant differences are reported ($\alpha=0.1$).

The exploratory investigation reported in table 6 reflects that there are some systematic differences between model parameters by demographic, attitudinal and behavioral variables. For this study, a brand manager interested in developing demographic profiles of a segment of the market based upon model parameters is therefore likely to find some systematic patterns. It should be recognized that new differences between groups may be discovered if the analysis is extended to more than one variable at a time. The one variable at a time analysis reported in table 6
demonstrates that the proposed framework provides machinery to conduct such an investigation.

Some of the differences reported in table 6 provide face validity for parameter estimates. For example it is seen that people who read labels or health conscious people are more salt content sensitive. Campbell buyers have a higher preference for Campbell than Progresso. Also, busy individuals or individuals who are on the lookout for new products to make their lives easier are more convenience sensitive as they prefer ready to serve soups to condensed soups. Table 6, however, also points out some interesting differences. For example Progresso is preferred more by males or by individuals with higher income. Younger individuals, individuals who eat dinner at home all the time or busy individuals tend to be more expenditure sensitive. Convenience oriented individuals, individuals who are on the lookout for new products to make their lives easier or individuals with high income are less price sensitive.

(ii) Primary demand analysis:

Table 6 clearly shows that there are systematic differences in model parameters between groups of individuals who participated in the survey. However, merely identifying these differences has limited value to a brand manager making product design and targeting decisions. The key advantage of the modeling framework used in this research is that it allows for an investigation of issues relating to primary demand. Specifically, it helps a brand manager relate product design changes to increase in market share and market size.
A price cut can affect sales at the brand level as well as the product category level. At the brand level, a price cut is likely to increase a brand’s sales because of consumer switching. This may be referred to as increase in secondary demand for the brand. At the product category level, a price cut is likely to increase a brand’s (and product’s) sales because of new consumers entering the market. This is referred to as increase in primary demand for the product.

It is of interest to a brand manager to investigate the impact of marketing mix elements on primary demand. In the framework developed in this research, this can be accomplished as follows. Consider a market comprising of two vegetable soup alternatives. The first alternative is Campbell brand, 60 calories/8 oz., ready to serve, 200 mg. salt/8oz. and priced at $3.50 for 4 servings. The second alternative is Progresso brand, 60 calories/8 oz., ready to serve, 200 mg. salt/8oz. and priced at $3.50 for 4 servings.

For the scenario described above, I studied the effect of a large $1.00 price cut by the Campbell brand on the primary and secondary demand. For the 185 respondents in the survey, it was found that a $1.00 price cut leads to the market size to increase by 36%. Market size was calculated as the sum of expected Campbell quantity and expected Progresso quantity for the 185 respondents. The market share for Campbell increased by 20%. The market share was calculated as the fraction of expected Campbell quantity divided by the sum of expected Campbell quantity and expected Progresso quantity. Of the total increase in expected Campbell quantity, 81% was due to an increase in primary
demand. The remaining 19% of the total increase in expected Campbell quantity was due to Progresso buyers switching to Campbell.

Next, let the Campbell brand manager be interested in studying the effect of the large price decrease of $1.00 on purchase quantity and purchase probability for the Campbell brand. The results of such an analysis appear in figures 3 and 4.

The distributions of expected quantity across the sample indicate an increase in quantity caused by a $1.00 price cut. The average increase in Campbell quantity is approximately 1 unit. The variability in this increase in quantity is helpful in identifying groups of individuals with the largest potential to increase their purchase quantity for Campbell. Another helpful diagnostic for a brand manager is based upon the purchase probability of buying the Campbell brand at the individual level. For a given product design and competitive choice set, the model provides individual level probability of buying a specific brand.

The distributions of probability of buying before and after a price cut are presented in figure 4. The distribution of the increase in purchase probability across the sample indicates a large variation across the sample. This suggests that there is a group of individuals with a large increase in probability of buying Campbell because of a $1.00 price cut.
FIGURE 4
PRIMARY DEMAND ANALYSIS: PURCHASE PROBABILITY
Figures 3 and 4 provide two valuable diagnostics to a brand manager. Figure 3 identifies the group of individuals with the largest quantity increase because of a price cut. These individuals contribute to the primary demand increase by increasing their quantity. Figure 4 identifies a group of individuals with the largest increase in their purchase probability. These people contribute to the primary demand increase by entering the market.

For targeting purposes, a brand manager needs to identify a set of variables which help discriminate between individuals with the largest increase in purchase quantity or purchase probability from the rest of the population. This can be accomplished fairly easily by developing a profile for individuals who reside in the tails of the distributions for quantity increase and purchase probability increase. Table 7 highlights the differences between individuals who have a large quantity sensitivity or a high purchase probability sensitivity as compared to the rest of the population.

In order to understand the differences in demographics, attitudes and behaviors, if any, the top 25% individuals in the distribution for quantity increase are compared with the remaining individuals in the sample. Similarly, the top 25% individuals in the distribution for purchase probability increase are compared with the remaining individuals in the sample. The profiles of individuals with large quantity or purchase probability sensitivity are developed based upon those descriptor variables on which the top 25% of the individuals are statistically different from the remaining 75%.
Table 7
Profiles of Individuals with Large Quantity and Purchase Probability Sensitivity

<table>
<thead>
<tr>
<th>Description</th>
<th>Demographics</th>
<th>Attitudes and Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 People with large quantity sensitivity</td>
<td>Less than 50 years of age</td>
<td>Eat at home all the time</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>Place importance on vegetables as part of dinner</td>
</tr>
<tr>
<td></td>
<td>Family size of three or more</td>
<td>Read labels</td>
</tr>
<tr>
<td></td>
<td>Family income of less than</td>
<td>Convenience oriented</td>
</tr>
<tr>
<td></td>
<td>$50,000</td>
<td>Busy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Want quick cooking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Look for new products</td>
</tr>
<tr>
<td>2 People with large purchase probability</td>
<td>More than 50 years of age</td>
<td>Eat at home sometimes</td>
</tr>
<tr>
<td>sensitivity</td>
<td>Male</td>
<td>Do not consider vegetables very important</td>
</tr>
<tr>
<td></td>
<td>Family size of two or less</td>
<td>Less convenience oriented</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less busy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quick cooking is not as important</td>
</tr>
</tbody>
</table>

In table 7 the top 25% individuals in the distribution for quantity increase are labeled “People with large quantity sensitivity”. This is reasonable since these individuals have the largest increase in expected Campbell quantity because of a $1.00 price cut. Similarly, the top 25% individuals in the distribution for probability of buying Campbell increase are labeled “People with large purchase probability sensitivity”. This is also reasonable since these individuals have the largest increase in purchase probability of buying Campbell because of a $1.00 price cut. Table 7 indicates that demographically, the individuals with large purchase quantity sensitivity are more likely to be younger, female and from lower income, large sized families. These individuals eat at home all the time, are busy, want quick cooking, are convenience oriented and look for new products to make their life easier. Also, these individuals are likely to place more importance on vegetables as part of dinner and are more likely to read labels.
On the other hand the individuals with large purchase probability sensitivity are more likely to be more than 50 years of age, male and from smaller sized families. These individuals eat at home sometimes, are less busy, do not want quick cooking and are less convenience oriented. Also, these individuals are likely to place less importance on vegetables as part of dinner.

The almost completely opposite profiles of individuals with large purchase probability sensitivity from those with large quantity sensitivity is explained by the fact that they are indeed different groups of people. The former were typically found to be non-buyers in the vegetable soup category where as the latter were typically found to be large quantity buyers.

(iii) Predictive test:

The proposed model was validated by using a predictive test. The model was re-estimated by using only 10 observations per person out of the available 12. The last two observations were saved as holdout observations for predictive testing. Two predictive statistics are reported in table 8. First, the mean absolute deviation (MAD) for choice probability for the two holdout observations, averaged across all 185 respondents, is reported. Second, the MAD for purchase quantity for the two observations, averaged across all 185 respondents, is reported. The MAD values for choice probability were calculated by taking the absolute value of the deviation of actual choice (i.e. a 0 or 1) from the choice probability predicted by the model. The MAD values for quantity were calculated by taking the absolute value of the deviation of actual quantity purchased from the quantity predicted by the model.
The two MAD statistics are compared for two separate models. The first model is the individual level hierarchical model presented in this dissertation. The second model is an aggregate model in which aggregate parameter estimates are used in the predictive exercise. Individual level heterogeneity is not considered in this model. This is accomplished as follows. In the second model, the mean vector of partworths ($\alpha$) is used instead of individual specific partworths. Further the parameter $\lambda_\mu$ is assumed to be a draw from the distribution $\text{Inverse Gamma}(\rho_\mu, \tau_\mu)$ and the parameter $\lambda_\kappa$ is assumed to be a draw from the distribution $\text{Inverse Gamma}(\rho_\kappa, \tau_\kappa)$. Therefore, the difference between the two models is that the first model recognizes heterogeneity among consumers and the second one ignores individual level differences.

### Table 8
Predictive Test

<table>
<thead>
<tr>
<th></th>
<th>Individual Model</th>
<th>Aggregate Model</th>
<th>Predictive Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean MAD in choice probability</strong></td>
<td>0.254</td>
<td>0.301</td>
<td>-0.047*</td>
</tr>
<tr>
<td><strong>Mean MAD in quantity</strong></td>
<td>1.97</td>
<td>2.33</td>
<td>-0.358*</td>
</tr>
</tbody>
</table>

* The predictive gain in MAD is significant at $\alpha=0.05$.

It is shown that the mean MAD for choice probability and quantity is 0.254 and 1.97 respectively. The individual model outperforms the aggregate model which ignores respondent heterogeneity. The approximate improvement in MAD for both choice
probability and quantity is nearly 15%. This difference is fairly substantial and statistically significant. The results in the predictive test demonstrate that the individual level estimates lead to more accurate predictions than aggregate estimates which ignore respondent heterogeneity. Therefore, the primary demand analysis of the type reported earlier, or any other analysis involving the proposed model should use individual level estimates.

(iv) Sensitivity analysis:

As stated during model development (equations 86 and 96), the price sensitivity parameter \( \mu \) and expenditure sensitivity parameter \( \kappa \) are constrained to be positive and above a minimum cut-off point. The reason for doing so is that at extremely small values (i.e. values close to zero) for \( \mu \) the choice probability (equation 83) approaches infinity. Similarly at extremely small values (i.e. values close to zero) for \( \kappa \) (or \( 1/ \beta_2 \)) the respondent expenditure (equation 57) approaches infinity.

Next, I study the effect of prior specification of the cut-off point for the distributions for \( \mu \) and \( \kappa \). Recall that for each person, \( \mu \) is distributed exponential (\( \lambda_{u} \)) with \( \mu > c_{m} \) and \( \kappa \) is distributed exponential (\( \lambda_{k} \)) with \( \kappa > c_{k} \). The sensitivity of individual specific parameters to the cut-off points \( c_{m} \) and \( c_{k} \) is investigated by comparing table 5 reported earlier to tables 9 and 10. Results in table 5 are based upon \( c_{m}=c_{k}=0.1 \). The cut off \( c_{m}=0.1 \) constrains the price elasticity to be less than 10. This is reasonable based upon the price elasticity range found by Rossi and Allenby (1994). The cut-off \( c_{k}=0.1 \) has no
Table 9
Sensitivity Analysis for Individual Level Model Parameters (c_m=c_k=0.2)

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>20</th>
<th>40</th>
<th>60</th>
<th>80</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand name partworth</td>
<td>0.77</td>
<td>0.10</td>
<td>-0.65</td>
<td>0.72</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.66)</td>
<td>(0.62)</td>
<td>(0.53)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>Calories partworth</td>
<td>-0.36</td>
<td>-0.32</td>
<td>-0.71</td>
<td>-1.51</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(0.57)</td>
<td>(0.51)</td>
<td>(0.65)</td>
<td>(0.59)</td>
</tr>
<tr>
<td>Ease of usage partworth</td>
<td>0.58</td>
<td>-0.43</td>
<td>-0.38</td>
<td>-0.25</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(0.51)</td>
<td>(0.52)</td>
<td>(0.50)</td>
<td>(0.54)</td>
</tr>
<tr>
<td>Salt content partworth</td>
<td>2.03</td>
<td>1.52</td>
<td>1.45</td>
<td>1.53</td>
<td>2.02</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.88)</td>
<td>(0.73)</td>
<td>(0.61)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>Mean of EV distribution(λ_m)</td>
<td>0.32</td>
<td>0.32</td>
<td>0.32</td>
<td>0.36</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.19)</td>
<td>(0.16)</td>
<td>(0.19)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Mean of Expenditure insensitivity(λ_n)</td>
<td>0.66</td>
<td>4.63</td>
<td>2.02</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(7.80)</td>
<td>(2.90)</td>
<td>(0.24)</td>
<td>(0.06)</td>
</tr>
</tbody>
</table>

Table 10
Sensitivity Analysis for Individual Level Model Parameters (c_m=0.1,c_k=0.2)

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>20</th>
<th>40</th>
<th>60</th>
<th>80</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand name partworth</td>
<td>0.85</td>
<td>-0.28</td>
<td>-0.63</td>
<td>0.76</td>
<td>-0.38</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.54)</td>
<td>(0.58)</td>
<td>(0.54)</td>
<td>(0.98)</td>
</tr>
<tr>
<td>Calories partworth</td>
<td>-0.32</td>
<td>-0.38</td>
<td>-0.69</td>
<td>-1.44</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.51)</td>
<td>(0.53)</td>
<td>(0.58)</td>
<td>(0.64)</td>
</tr>
<tr>
<td>Ease of usage partworth</td>
<td>0.55</td>
<td>-0.58</td>
<td>-0.39</td>
<td>-0.24</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.47)</td>
<td>(0.48)</td>
<td>(0.46)</td>
<td>(0.57)</td>
</tr>
<tr>
<td>Salt content partworth</td>
<td>1.92</td>
<td>1.22</td>
<td>1.31</td>
<td>1.49</td>
<td>2.18</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.68)</td>
<td>(0.74)</td>
<td>(0.54)</td>
<td>(0.69)</td>
</tr>
<tr>
<td>Mean of EV distribution(λ_m)</td>
<td>0.38</td>
<td>0.30</td>
<td>0.34</td>
<td>0.43</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.17)</td>
<td>(0.19)</td>
<td>(0.25)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>Mean of Expenditure insensitivity(λ_n)</td>
<td>0.65</td>
<td>1.47</td>
<td>1.75</td>
<td>0.32</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(2.09)</td>
<td>(3.80)</td>
<td>(0.23)</td>
<td>(0.06)</td>
</tr>
</tbody>
</table>
interpretive meaning and should therefore be viewed as a mathematical constraint to make the model tractable.

Based upon the sensitivity analysis it is seen that the same pattern in parameter estimates emerges from tables 5, 9 and 10. The same parameter estimates are statistically significant across the three tables. None of the statistically significant parameters are different ($\alpha=0.05$) across the three tables.

In summary, the objectives of empirical analyses in this chapter were to estimate the parameters of the model proposed in chapter III, demonstrate how the model can be used to study primary demand and test the predictive ability of the model. I began with a description of the study and the data collection procedure used in this dissertation. Tables 3, 4 and 5 report the parameter estimates. Figures 3 and 4 demonstrate how the model can be used to study primary demand. Finally, table 8 reports results for a predictive test. Next, I discuss the conclusions drawn from the empirical analyses.
CHAPTER V
Conclusions

From the perspective of a brand manager with the objective of increasing brand sales it is important to develop an understanding of three consumer related questions. First, what are the factors which drive a consumer to purchase or not purchase from a given product category? Second, for a consumer who does purchase from the given product category what is the relationship between product characteristics of the available alternatives and her purchase quantity? And third, what are the trade-offs that the given consumer makes between product attributes in order to make a choice decision?

Typical choice models (McFadden 1973, Guadagni and Little 1983) condition on the purchase event and focus on the effect of differences in the available alternatives on consumer choice. Other aspects of the purchase decision such as purchase/non-purchase and purchase quantity are usually not considered. Although an analysis based upon choice models conditional on the purchase event is informative about trade-offs that a consumer makes between the available alternatives, it is not informative about why the consumer chooses to buy or not buy from a product category. Also, it does not provide any insights into the relationship between the attributes of the available alternatives and purchase quantity.
By jointly modeling consumer choice, purchase/non-purchase and quantity decisions I develop a framework which can help a brand manager develop answers to the three consumer related questions raised above. As seen in figure 4, the framework relates a product design change to the change in probability that a consumer will buy the given brand. In addition, figure 3 relates a design change to the change in purchase quantity. The unique advantage of the framework is that the analysis is conducted at the individual level. This allows a brand manager to identify individuals with the largest potential to either start buying from the product category or increase purchase quantity.

The framework, therefore, helps in identifying two separate groups of individuals with the highest potential to increase primary demand. The first group comprises of individuals who currently have a low probability to be buyers of the given brand but have the largest potential increase in their probability to buy. The second group comprises of individuals who are currently buyers in the product category but have the highest potential to increase their purchase quantity. The demographic, attitudinal and behavioral profiles of the individuals with the largest potential (Table 7) can then be used to identify the target market for a marketing action such as product repositioning or new product introduction.

A price cut can affect sales at the brand level as well as the product category level. At the brand level, a price cut is likely to increase a brand’s sales because of consumer switching. This may be referred to as increase in secondary demand for the brand. At the product category level, a price cut is likely to increase a brand’s (and product’s) sales because of new consumers entering the market. This is referred to as increase in primary
demand for the product. By jointly considering purchase/non-purchase, quantity and choice decisions of consumers, a brand manager will come up with a marketing strategy which enhances total brand sales. This will be accomplished by increasing market share as well as market size. Such a strategy would focus on increasing primary demand of a product, in addition to increasing the brand’s market share.

An assumption which is implicit in the model specification may warrant further investigation. Because of the linear and additive bivariate utility specification, the model assumes that a consumer chooses only one brand from the available choice set. This may be restrictive if a consumer indulges in variety seeking behavior. An alternative model specification may be explored in order to overcome the restriction imposed by this assumption.

In summary, this research makes a significant methodological and substantive contribution to the marketing literature. The first methodological contribution of the dissertation is that it provides individual level estimates of reservation value and expenditure sensitivity parameters. The reservation value relates product design to the purchase/non-purchase decision of an individual and the expenditure sensitivity parameter relates product design to the purchase quantity of an individual. Chiang (1991) and Chintagunta (1993) also exploit the notion of reservation value (or price) but their approaches do not provide individual level estimates. A hierarchical Bayes model is used to estimate the proposed model at the individual level. Recent advancements in simulation based methods are used to overcome the computational difficulties associated
with estimating hierarchical Bayes models. A unique advantage of the Bayesian formulation is that it provides empirical posterior distributions of individual level reservation value and expenditure sensitivity. Statistical properties of these individual level estimates can be easily studied from the posterior distributions. It is the inference at the individual level which allows me to investigate issues related to primary demand.

The second methodological contribution is to establish a link between conjoint methodology and the consumer decision of how much to buy. Traditionally, the use of conjoint analysis has been restricted to understanding the consumer choice decision only. By combining microeconomic theories with conjoint analysis, this dissertation studies consumer decisions of what to buy and how much to buy in a single unifying framework. The value of such a framework is that it provides additional information regarding marketing decisions. For example, the traditional conjoint analysis is useful in identifying individuals who are most likely to buy a given product design. The proposed framework, in addition to identifying the most likely buyers, also helps in identifying individuals who are most likely to buy large quantities of a given product design.

The substantive contribution of the dissertation is that it provides a formal framework to understand the link between product design and primary demand. From a brand manager's perspective, the framework assists in developing a product design strategy which increases total brand sales by increasing market share as well as the market size. Analysis at the individual level helps in identifying those consumers who have the largest potential to increase primary demand. A demographic, attitudinal or
behavioral profile of these consumers can be used for targeting purposes. The framework is therefore useful for product introduction and/or product repositioning decisions.
APPENDIX A

Questionnaire
SOUP ATTITUDE STUDY

May, 1995

Respondent's Name

Address

City/State Zip Code

Telephone Number Date

Interviewer's Signature

CARD 1 = COL. 64(1)

Hello, I'm of a national market research firm. We are doing a survey on soups, and I'd like to ask you a few questions.

1a. Into which of the following age groups do you fall? (READ LIST AND RECORD BELOW)

   Under 21 . . . . . . . ( ) -> (TERMINATE AND TALLY)
   21 - 30 . . . . . . . 6 ( )-1
   31 - 40 . . . . . . . ( )-2
   41 - 50 . . . . . . . ( )-3
   51 - 60 . . . . . . . ( )-4
   61 - 70 . . . . . . . ( )-5
   71 years or older ( )-6

1b. INDICATE RESPONDENTS' GENDER:

   Male... 9( )-1
   Female... ( )-2

2. Do you and your household eat dinner at home... (READ LIST)?

   All the time . . . . . . . 10 ( )-1
   Sometimes . . . . . . . . ( )-2
   Never . . . . . . . . . . . ( ) -> (TERMINATE AND TALLY)

3. I am interested in understanding the purchase patterns for vegetable soup for you and your household. Specifically, I am interested in learning about consumption of vegetable soup to have with dinner for you and your household.

First, I will show you descriptions of some vegetable soups in terms of their product characteristics. I will describe each type of vegetable soup in terms of its brand name, calorie content, ease of usage, salt content and price.

Brand Name: There are two soup brand names that this study will focus on -- Progresso and Campbell.

Calorie Content: A soup can be hearty, contain lots of vegetables and have nearly 120 calories per 8 oz. serving. On the other hand, it can be light, be used on a relatively thinner broth and have nearly 60 calories per 8 oz. serving.

Ease Of Usage: A soup may come in a condensed or a ready-to-serve form. Condensed soup requires some cooking effort whereas a ready-to-serve vegetable soup requires minimal cooking effort.

Salt Content: An 8 oz. serving of vegetable soup considered in this study may have either 200 mg. or 800 mg. of sodium.

Price: The price is indicated in terms of dollars for four 8 oz. servings (i.e. dollars per 32 oz.).

A typical product description would look like: (SHOW CARD #1)

Progresso

Hearty (120 calories)
Condensed
200 mg. salt
$2.50 for 4 servings

This vegetable soup has the brand name Progresso, has 120 calories per serving, is in a condensed form, has 200 mg. salt per serving and is priced at $2.50 for 4 servings.

I will show the vegetable soup descriptions to you in pairs and ask you to select the product which you prefer.
4. Please look at these two descriptions of vegetable soup. Which one of these would you prefer? (Record below under Col. Q.4.)

(Insert product preferred in Q.4 when asking Q.5. Do not ask Q.5 for product not preferred in Q.4.)

5. Would you buy this vegetable soup for consumption by you and your household to have with dinner? (Record below under Col. Q.5.)

(Insert product preferred in Q.4 and would buy in Q.5. Do not ask if would not buy in Q.5.)

6. In an average winter month, that is, an average 4 week period in the winter, how many times would you or your household consume this vegetable soup at dinner? (Record exact number under Col. Q.6.)

Repeat questions 4, 5 and 6 for each pair listed

<table>
<thead>
<tr>
<th>(Start Here)</th>
<th>Col. Q.4</th>
<th>Col. Q.5</th>
<th>Col. Q.6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Product Preferred</td>
<td>Would Buy</td>
<td>Would Buy Not Buy</td>
</tr>
<tr>
<td>1. Product A</td>
<td>( )-1</td>
<td>( )-1</td>
<td>( )-1</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-2</td>
<td>( )-2</td>
<td>( )-2</td>
</tr>
<tr>
<td>2. Product A</td>
<td>( )-3</td>
<td>( )-3</td>
<td>( )-3</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-4</td>
<td>( )-4</td>
<td>( )-4</td>
</tr>
<tr>
<td>3. Product A</td>
<td>( )-5</td>
<td>( )-5</td>
<td>( )-5</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-6</td>
<td>( )-6</td>
<td>( )-6</td>
</tr>
<tr>
<td>4. Product A</td>
<td>( )-7</td>
<td>( )-7</td>
<td>( )-7</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-8</td>
<td>( )-8</td>
<td>( )-8</td>
</tr>
<tr>
<td>5. Product A</td>
<td>( )-9</td>
<td>( )-9</td>
<td>( )-9</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-0</td>
<td>( )-0</td>
<td>( )-0</td>
</tr>
<tr>
<td>6. Product A</td>
<td>( )-x</td>
<td>( )-x</td>
<td>( )-x</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-y</td>
<td>( )-y</td>
<td>( )-y</td>
</tr>
<tr>
<td>7. Product A</td>
<td>12</td>
<td>( )-11</td>
<td>( )-11</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-2</td>
<td>( )-2</td>
<td>( )-2</td>
</tr>
<tr>
<td>8. Product A</td>
<td>( )-3</td>
<td>( )-3</td>
<td>( )-3</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-4</td>
<td>( )-4</td>
<td>( )-4</td>
</tr>
<tr>
<td>9. Product A</td>
<td>( )-5</td>
<td>( )-5</td>
<td>( )-5</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-6</td>
<td>( )-6</td>
<td>( )-6</td>
</tr>
<tr>
<td>10. Product A</td>
<td>( )-7</td>
<td>( )-7</td>
<td>( )-7</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-8</td>
<td>( )-8</td>
<td>( )-8</td>
</tr>
<tr>
<td>11. Product A</td>
<td>( )-9</td>
<td>( )-9</td>
<td>( )-9</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-0</td>
<td>( )-0</td>
<td>( )-0</td>
</tr>
<tr>
<td>12. Product A</td>
<td>( )-x</td>
<td>( )-x</td>
<td>( )-x</td>
</tr>
<tr>
<td>Product B</td>
<td>( )-y</td>
<td>( )-y</td>
<td>( )-y</td>
</tr>
</tbody>
</table>
7. Now I'd like you to tell me whether you agree or disagree with each of the following statements. There are no right or wrong answers. We are just interested in your opinions. The (first/next) statement is... (READ "X'ED" STATEMENT). Do you agree or disagree with this statement? (OBTAIN RESPONSE) Is that completely or somewhat? (RECORD ONE RESPONSE BELOW. CONTINUE UNTIL ALL STATEMENTS HAVE BEEN ASKED. DO NOT READ "NEITHER AGREE NOR DISAGREE" BUT ALLOW FOR RESPONSE.)

(START HERE) Agree Agree Neither Disagree Disagree

- I consider myself to be health conscious ...
- I usually read the labels on food packaging before deciding what to buy ...
- Convenience is an important factor in all my purchase decisions ...
- My life is a constant flurry of activities ...
- I rarely think about my health ...
- My main interest in cooking is getting it done faster ...
- There never seems to be enough time to do everything ...
- I am always on the lookout for new products that will make my life easier ...

8a. Do you buy vegetable soup for you and your household?

Yes... 71 ( )-1
No... ( )-2

8b. What brands of vegetable soup do you buy? (DO NOT READ LIST) (RECORD ALL THAT APPLY BELOW)

- Campbell ...
- Healthy Choice ...
- Lipton ...
- Progresso ...
- Other (SPECIFY) ...

9a. How important to you are vegetables as part of dinner? Would you say vegetables are an extremely important part of dinner, a very important part of dinner, a somewhat important part of dinner or a not at all important part of dinner? (REPEAT CHOICES AS NECESSARY) (RECORD ONE RESPONSE BELOW)

- Extremely important ...
- Very important ...
- Somewhat important ...
- Not at all important ...

9b. And would you say you have vegetables in some form with dinner always, sometimes, rarely or never? (REPEAT CHOICES AS NECESSARY) (RECORD ONE RESPONSE BELOW)

- Always ...
- Sometimes ...
- Rarely ...
- Never ...

10. How often do you have dinner with the family? That is, how many days in an average week, does your family eat together? (CIRCLE EXACT NUMBER BELOW)

75- 0 1 2 3 4 5 6 7
There are just a few questions for classification purposes only.

A. Would you please tell me the grade of school you last completed?  (READ LIST AND RECORD BELOW)

<table>
<thead>
<tr>
<th>Grade school or less</th>
<th>8 ( )-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Some high school</td>
<td>( )-2</td>
</tr>
<tr>
<td>Completed high school</td>
<td>( )-3</td>
</tr>
<tr>
<td>Some college</td>
<td>( )-4</td>
</tr>
<tr>
<td>College graduate</td>
<td>( )-5</td>
</tr>
<tr>
<td>Other (SPECIFY:)</td>
<td>( )-6</td>
</tr>
</tbody>
</table>

(READ QUESTION AS APPLIED)  (DO NOT READ) Refused  ( )-y

B-1. Are you currently employed?

<table>
<thead>
<tr>
<th>Yes</th>
<th>9 ( )-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>( )-2</td>
</tr>
<tr>
<td>Retired</td>
<td>( )-3</td>
</tr>
</tbody>
</table>

(READ QUESTION AS APPLIED)  (DO NOT READ) Refused  ( )-y

B-2. In a typical week, how many hours would you say you work?

10/11- (# HOURS WORK PER WEEK)

B-3. In what field or industry do you work?

12-  
13-  

B-4. What is your Job title?

14-  

C-1. What is your marital status? Are you... (READ LIST)? (RECORD BELOW)

<table>
<thead>
<tr>
<th>Married</th>
<th>15 ( )-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Living with someone of the opposite sex</td>
<td>( )-2</td>
</tr>
<tr>
<td>Single (never married)</td>
<td>( )-3</td>
</tr>
<tr>
<td>Separated</td>
<td>( )-4</td>
</tr>
<tr>
<td>Widowed/divorced</td>
<td>( )-5</td>
</tr>
</tbody>
</table>

(READ QUESTION AS APPLIED)  (DO NOT READ) Refused  ( )-y

C-2. Is your spouse currently employed/Is the person you live with currently employed?

<table>
<thead>
<tr>
<th>Yes</th>
<th>16 ( )-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>( )-2</td>
</tr>
<tr>
<td>Retired</td>
<td>( )-3</td>
</tr>
</tbody>
</table>

(READ QUESTION AS APPLIED)  (DO NOT READ) Refused  ( )-y

C-3. In a typical week, how many hours does (he/she) work?

17/18- (# HOURS WORK PER WEEK)
C-4. In what field or industry does (he/she) work?

______________________________   39-

C-5. What is (his/her) job title?

______________________________   21-

D. Including yourself, how many are there in your family now living at home?
(CIRCLE RESPONSE)

22- 1 2 3 4 5 6 7 8 9 or more

E. Would you please tell me the income group which best describes your total
family income? (READ LIST AND RECORD BELOW)

Under $20,000 . . . . . . . . . . . . . . . 23 ( )-1
$20,000 to under $30,000 . . . . . . . ( )-2
$30,000 to under $40,000 . . . . . . . ( )-3
$40,000 to under $50,000 . . . . . . . ( )-4
$50,000 to under $60,000 . . . . . . . ( )-5
$60,000 to under $70,000 . . . . . . . ( )-6
$70,000 and over . . . . . . . . . . . . ( )-7
(Do NOT READ) → Refused . . . . . . . . . ( )-y

F. And finally, in order to be sure we have representatives of all groups, how
may we classify you by race? (READ LIST AND RECORD BELOW)

White . . . . . . . . . . . . . . . . . . . . . 24 ( )-1
African-American . . . . . . . . . . . . ( )-2
Asian . . . . . . . . . . . . . . . . . . . . ( )-3
Hispanic . . . . . . . . . . . . . . . . . . ( )-4
Other . . . . . . . . . . . . . . . . . . . . ( )-5

Thank you very much for your time and cooperation. Your opinions will be
very helpful.
APPENDIX B

Conjoint Exercise
A

1. Progresso
   Light (60 calories)
   Condensed
   800 mg salt
   $1.20 for 4 servings

B

   Campbell
   Hearty (120 calories)
   Ready to serve
   200 mg salt
   $3.00 for 4 servings

A

2. Light (60 calories)
   Campbell
   Condensed
   800 mg salt
   $1.40 for 4 servings

B

   Hearty (120 calories)
   Progresso
   Ready to serve
   200 mg salt
   $2.00 for 4 servings

A

3. $1.60 for 4 servings
   800 mg salt
   Light (60 calories)
   Ready to serve
   Progresso

B

   $2.20 for 4 servings
   800 mg salt
   Hearty (120 calories)
   Condensed
   Campbell
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.</td>
<td>Condensed</td>
<td>Ready to serve</td>
</tr>
<tr>
<td></td>
<td>$1.40 for 4 servings</td>
<td>$2.60 for 4 servings</td>
</tr>
<tr>
<td></td>
<td>Progresso</td>
<td>Campbell</td>
</tr>
<tr>
<td></td>
<td>Hearty (120 calories)</td>
<td>Light (60 calories)</td>
</tr>
<tr>
<td></td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td></td>
<td>Campbell</td>
<td>Progresso</td>
</tr>
<tr>
<td></td>
<td>Hearty (210 calories)</td>
<td>Light (60 calories)</td>
</tr>
<tr>
<td></td>
<td>Condensed</td>
<td>Ready to serve</td>
</tr>
<tr>
<td></td>
<td>$2.00 for 4 servings</td>
<td>$1.80 for 4 servings</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>$3.60 for 4 servings</td>
<td>$3.40 for 4 servings</td>
</tr>
<tr>
<td></td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td></td>
<td>Campbell</td>
<td>Progresso</td>
</tr>
<tr>
<td></td>
<td>Hearty (120 calories)</td>
<td>Light (60 calories)</td>
</tr>
<tr>
<td></td>
<td>Ready to serve</td>
<td>Condensed</td>
</tr>
</tbody>
</table>
7. Progresso
   Light (60 calories)
   Ready to serve
   800 mg salt
   $1.60 for 4 servings

   Campbell
   Hearty (120 calories)
   Condensed
   200 mg salt
   $2.30 for 4 servings

8. Ready to serve
   Light (60 calories)
   Campbell
   800 mg salt
   $2.20 for 4 servings

   Condensed
   Hearty (120 calories)
   Progresso
   200 mg salt
   $1.90 for 4 servings

9. Progresso
   $3.20 for 4 servings
   Hearty (120 calories)
   Ready to serve
   800 mg salt

   Campbell
   $3.00 for 4 servings
   Light (60 calories)
   Condensed
   800 mg salt
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td></td>
<td>Hearty (120 calories)</td>
<td>Light (60 calories)</td>
</tr>
<tr>
<td></td>
<td>Ready to serve</td>
<td>Condensed</td>
</tr>
<tr>
<td></td>
<td>Progresso</td>
<td>Campbell</td>
</tr>
<tr>
<td></td>
<td>$2.20 for 4 servings</td>
<td>$1.90 for 4 servings</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>Ready to serve</td>
<td>Condensed</td>
</tr>
<tr>
<td></td>
<td>Campbell</td>
<td>Progresso</td>
</tr>
<tr>
<td></td>
<td>Hearty (120 calories)</td>
<td>Light (60 calories)</td>
</tr>
<tr>
<td></td>
<td>$2.60 for 4 servings</td>
<td>$1.30 for 4 servings</td>
</tr>
<tr>
<td></td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>Light (60 calories)</td>
<td>Hearty (120 calories)</td>
</tr>
<tr>
<td></td>
<td>Condensed</td>
<td>Condensed</td>
</tr>
<tr>
<td></td>
<td>800 mg salt</td>
<td>200 mg salt</td>
</tr>
<tr>
<td></td>
<td>Campbell</td>
<td>Progresso</td>
</tr>
<tr>
<td></td>
<td>$3.00 for 4 servings</td>
<td>$2.80 for 4 servings</td>
</tr>
</tbody>
</table>
LIST OF REFERENCES


