Conjoint and Discrete Choice Designs for Pricing Research.

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1 Introduction to Pricing Research

Pricing decisions faced by most managers are challenging and create uncertainty for their respective organization. The main purpose of this note is to describe conjoint analysis and related methods, so that managers can interpret results from conjoint studies and make better market place decisions. There is extensive discussion and writing about the details of pricing decisions and their implications. Consider following reality. Pricing decisions affect both revenue and profitability that is because price influences the level of demand at the brand as well as the product category level. Consequently, academic as well as market researcher have shown a great deal of interest in understanding customer price sensitivity.

Price also communicates value. From the customer's point of view, value is the bundle of benefits for which a specific price is paid. If the customer were to receive only a single benefit, then price and value trade-off would be relatively easy. However, for most products and services for which marketing plays a critical role, the customer often receives multiple benefits. Consequently, one needs a tool to measure the trade-off between price and value. As will be shown below, conjoint analysis is an efficient and effective approach to understand the customer's price and value trade-off.

This note is organized in two parts. The first part is a broad introduction to a versatile tool referred to in the literature as conjoint analysis. There are many variations and often many confusing names used by researchers. Discrete choice analysis, trade-off analysis, price-value trade-off are some of names used instead of conjoint analysis. These names may imply different procedural details, all methods generally provide a "willingness to give-up something for gaining something else". This is the central idea behind conjoint and related methods.

The second part of this note is a tutorial that allows reader to assess his / her own values for two products. By completing this tutorial, one should be able to judge whether conjoint or discrete choice is a useful tool, whether conjoint analysis is able to portray his / her own values. Although tutorial is meant to help reader understand and interpret conjoint results, it is not meant as a tool to design conjoint study.

[1]The basic structure of this guide (pages 1 to 18) is based on "Conjoint Analysis: A Manager's Guide", by Robert J. Dolan, Harvard Business School, case no. 590-059, 1990. Author would like to thank Lianxi Zhou and Anne Wilcock for their comments to earlier version of this document.

2 Introduction to Conjoint Analysis

If one were to argue that "life is a trade-off", then conjoint analysis is the tool to measure it. Over the last 30 years, market researchers have developed conjoint analysis to understand customer preferences, values and choices. Conjoint analysis is used for many marketing decisions, including new product development process, selecting among alternative product designs, targeting, and pricing. Several studies have documented that conjoint and discrete choice models are well accepted in marketing in North America and in Europe (see, Cattin and Wittink 1982, Wittink and Cattin 1989, Wittink, Vriens and Burhenne 1994). Applications have covered many industries and virtually all aspects of managerial decision making. Some consulting firms use expertise in this technique as a competitive advantage, even when the basic technique has been known for over 30 years. The following is a list of a few published studies that have used conjoint analysis recently:

- Internet-based product concept test (Dahan and Srinivasan 2000).
- Supply chain design (Reutterer and Kotzab 2000).
- Venture capital projects and profitability (Shepherd, Ettenson and Crouch 2000).
- Design of electronic toll collection, EZPass (Vavra, Green and Krieger 1999).
- Work flow design to implement quality function deployment (QFD) (Gustafsson, Ekdhl and Bergman 1999)
- Design of product platform (Moore, Louviere and Verma 1999).
- Optimal tariff charges for cell phones (Jain, Muller and Vilcassim 1999).

In recent years, conjoint analysis has also received attention from health and environmental researchers. In health care field, researchers have looked at medical decision making (for example, evaluation of alternative treatments) as well as health care management (for example, evaluation of features of health insurance). Similarly, in the environmental field researchers have expanded their efforts to understand consumers' willingness to pay for "priceless" (for example, value scenic beauty) as well as insurance and liability issues arising from possible environmental damages. Conjoint analysis has become a tool in the repertoire of all major market research firms and within many companies. Easy-to-use software packages are widely available. This note provides an introduction to the method and steps involved in conducting conjoint studies. Section 2 explains the concepts underlying the procedure, that is, *the decomposition of a product into its attributes and subsequent valuation of the utility of each individual attribute.* Section 3 covers derivation of meaningful managerial implications from conjoint results. Section 4 discusses the accuracy of the methods and Section 5 provides strengths and weaknesses of the general method.

3 Basic Concepts Underlying Conjoint Analysis.

3.1 Defining a Product or Service

Most products and services are composed of a set of relevant attributes. For example, Vavra et al. (1999) describe an electronic toll collection system, EZPass in terms of seven attributes:

1. Number of lanes available and control of each,
2. Price of the toll with EZPass,
3. Process of obtaining a new account (how / where to apply and pay),
4. The acquisition cost for EZPass,
5. Number of EZPass accounts and invoice timing,
6. Transfer of EZPass to other vehicles, and
7. Other potential uses for the EZPass (discounts, merchandise etc.).

By defining products as collections of attributes and having the individual consumer react to a number of alternatives, one can infer each attribute's (i) importance and (ii) most desired level for *each consumer*. It is important to note that one can understand and calibrate conjoint models for each customer. In the appendix attached to this note the reader may calibrate his / her own importance and most desired levels for a camcorder and a chocolate bar.

Conjoint analysis provides a method to assess an individual's "value system," which specifies directly or indirectly the monetary value a consumer puts on each level of each of the attributes. If we know an individual's value system, we can predict which of a set of available alternatives the individual might buy. The main idea in conjoint analysis is to construct the value system by asking about preferences on a small subset of products and then using the system to make predictions about relative preferences for any products that are plausible and could be sold in the market place. This will become clearer as ideas are presented below. First, we consider how one can calculate a "value system" from some overall judgments.

For example, consider a pricing problem facing the banking industry. Two attributes are potentially important to consumers: (i) transaction mode and (ii) cost per transaction. There are two alternative "levels" for cost per transaction (free and $0.20) and three levels for transaction mode:

1. Automatic teller machines banking (ATMB)
2. Automated telephone banking (ATB)
3. Internet based banking (IBB)

Table 1: Individual Rankings

		Cost per Use: free	Cost per Use: $0.20
Mode	Machine (ATMB)	Rank 6	Rank 4
	Telephone (ATB)	Rank 5	Rank 3
	Internet (IBB)	Rank 2	Rank 1

There are thus $2 \times 3 = 6$ different mode/cost combinations or products. One might in practice ask individuals how important these alternative attributes are. Alternatively, one can simply ask the respondent to rank order the six possible combinations from most(6) to least preferred (1). The individual might provide ranks as shown in Table 1. Note that these rankings do not represent a statistical summary but rather the preferences expressed by one individual.

Table 2
Derived Value System

		Cost: free	Cost: $0.20	
Mode	ATMB	5	3	Average = 4
	ATB	4	2	Average = 3
	IBB	1	0	Average = 0.5
	Average	3.33	1.67	

With these ranks, we can assign utility points (where higher is better) to the options to capture these expressed preferences. For example, we might code the best as 5 points and then go down from there, so the least desired alternative would be assigned a zero. That would yield preference ratings as given in Table 2.

Table 3
Value System

Cost per transaction		
	Free =	3.33
	$0.20 =	1.67
Transaction Mode		
	ATMB =	4
	ATB =	3
	IBB =	0.5

Since each transaction mode is ranked with both levels of the cost per transaction attribute, we can calculate the utility of an attribute level as the average of the score across all choices where it appears. Using this procedure, we would obtain summary as given in Table 3.
This is the individual's "value system". Note that it recaptures the stated original ranking data and comparison is provided in Table 4.

This is the objective of the procedure, that is, to have an individual provide overall preference judgments for various products and then use mathematical analysis to tease out the individual's underlying "value system," that is, the value of each level of each attribute. The procedure allows us to assess a consumer's willingness to trade off one feature for another. The value system shows that this individual is averse to the idea of internet banking (IBB = 0.5) and would be unwilling to trade in telephone banking (since at minimum this decreases this individual's utility by 3 - .5 = 2.5 points) in order to get "free" banking service (since this increase individual's utility by only 3.33 - 1.67 = 1.66).

Table 4
Prediction from Value System

Product	Value System Score	Value System Score Rank	Stated Original Rank
ATMB + Free	4 + 3.33 = 7.33	1	1
ATB + Free	3 + 3.33 = 6.33	2	2
ATMB + $0.20	4 + 1.67 = 5.67	3	3
ATB + $0.20	3 + 1.67 = 4.67	4	4
IBB + Free	.5 + 3.33 = 3.83	5	5
IBB + $0.20	.5 + 1.67 = 2.17	6	6

This simple example is meant only to provide some intuition for how the procedure works. In the appendix attached with these notes, several examples are provided to allow the reader to calibrate his or her own value system. The trade-off matrix approach (proposed by Johnson 1974) is useful for problems with a small number of attributes, each with a small number of alternative levels (see examples with four or five attributes in appendix). Slightly different approaches work better for larger scale problems. Although not demonstrated in our example, a key point is that the respondent need not rank all possible products in order to be able to derive the value system. For example, Green and Wind's (1975) respondents ranking of 18 products allowed the estimation of a value system for a product of five attributes (3 attributes with 3 levels and 2 attributes with 2 levels). With the value system, however, one could then predict the preference for the $3 \times 3 \times 3 \times 2 \times 2 = 108$ possible products.

3.2 Alternatives to Conjoint Analysis

There are a number of alternatives to conjoint analysis. For example, we may ask questions about a respondent's willingness to pay for a product or service or observe actual choice(s) in the market place. Note that modifying products or services in the market place is not only costly but also sometime not practical. For example, it is not practical to offer the same product for two or more different prices. In order to understand attribute valuation, the market researcher might resort to direct questioning for preferences. For example, do you prefer a product with the "Made in Canada" label? Consumers may find it easy to state their preferences but their responses may have limited or no predictive value for product choices in the market place. Rather than forcing consumers to think separately about individual attributes, and their levels in isolation, conjoint analysis asks the consumer to make judgments about products overall and then uses mathematical analysis to uncover the value system which must be behind the preference judgments.

Another alternative commonly used in the health and environmental area is to ask direct questions about the amount a consumer is willing to pay for a product and / or service. In the pricing area, a similar approach is used in the price metering technique. While asking respondents about their willingness to pay is a simple approach, respondents may base their

judgments on prior product experience or may even be insensitive to product attribute such as brand name.
The term "conjoint analysis" applies to a variety of procedures developed to calibrate an individual's value system from overall product judgments. The remainder of this section covers input data and data analysis alternatives.

3.3 Study Design

A conjoint study has following six design stages.

1. Determine *Relevant Attributes and their levels*.
2. Determine *Product Presentation: Content and Form*.
3. Determine *Respondent - Researcher Interaction format*.
4. Decide on *Response Type*, rating, ranking, or choice.
5. Determine *Criterion* for judging, liking, purchasing or willing to pay.
6. Decide on *Data Analysis Technique*.

3.3.1 Relevant Attributes and their levels

In conjoint, the researcher must specify the attributes that influence customer decisions. If one included an attribute that has no real importance to most customers, the value system will reflect that. On the other hand, in the conjoint analysis, it may be very difficult to detect the absence of an important attribute. Consequently, the researcher must be confident that the set of attributes that has been included is reasonably complete. To accomplish such a task, the preliminary attribute list is usually developed by the researcher using contact with company people from different functional areas including new product development, advertising, and manufacturing. Some researchers advocate using all attributes that are known to consumers and feasible for change and note that there are four kinds of attributes that could be potentially used in conjoint studies:

1. Physical attributes - refers to the product itself, for example, product weight or size.
2. Performance benefit - refers to outcome, for example, kilometers per litre.
3. Cost-based attributes - refers to cost of acquiring the product or service or cost associated with continuing to use the service. This includes installation cost as well as monthly charges or fees.
4. Psychological positioning - refers to user perception, for example, assurance.

Although the above list suggests only four types of attributes, the actual list of attributes is likely to be longer. For example, in a recent study involving retail credit cards, it was noted that credit cards have about 40 different attributes. Inclusion of all of these attributes in a study for all respondents is neither practical nor economically feasible. Consequently, other researchers have argued that "the stimuli descriptions must convey all the information that respondents feel they need to make their decisions." Consequently, it may be helpful to conduct customer research project to understand the key attributes prior to conducting the conjoint study. From a managerial perspective, one may focus on attributes that are proposed for change and feasible to implement. In such a case, one may consider attributes that are important to customers and managers.

To illustrate the nature of the trade-off involved, consider a study dealing with health insurance which was based on 23 attributes with three levels and one attribute with six levels (Chakraborty, Ettenson and Gaeth 1994). The resulting service descriptors were long and it is likely that one would require a large sample (at least several hundred) to understand customer preferences for all the attributes. On the other hand, by focusing on three-to-five key attributes, one may be able to understand the customer value system using a small sample (less than 25). With presentation of many attributes simultaneously, respondents are going to face the difficult task of understanding the product description and then assigning ranks or rating scores or making choices. If a study contains many attributes and the study analyst is unwilling to reduce the set of attributes to between four and seven, product presentation (see section 3.3.2) must be made together with the choice of attributes. Another alternative is to let the respondent choose the top four-to-seven attributes. In such a case, each respondent is offered a different conjoint study.

One attribute that is central to marketing is brand name. If estimates concerning market share and / or competitive opportunities and threats are critical, one should include brand as one of the conjoint attribute. Similarly, when there are many brands in the market place (for example, shampoo) or there are number brands with high degree of brand loyalty or brands have high and low perceived value, one may have to include brand name. On the other hand, many researchers, especially studying patient preferences for prescription drugs, prefer not to use brand name in conjoint research. This is because brand name can be powerful identifier to customers which in turn may reduce the likelihood of trade-off among other important product attributes. In conclusion, brand name should be used in conjoint studies to assess brand value and equity.

3.3.2 Product Presentation: Content and form

The second design question is how to present products to the respondent: partial or full profile method and presentation form. In the full profile approach, each product is described in terms of all the relevant attributes. An example of this is Seaton and Laskey's (1999) study of perceived value of production location of automobiles. A total of 266 consumers rated 34 cars which contained a description on seven attributes. A sample rating task is shown below.

Brand: **MITSUBISHI**

Country of component manufacture *USA.*
Discount price of *4% off list price of $17,000.*
Country of assembly *USA.*
Driving distance of dealership *10 minutes.*
Dealership "reliability" *often requires a second visit.*
Dealership "empathy" *personalized customer attention.*

Would you consider buying such car?
(Circle the number that best represents your response).

would definitely not consider buying										Would definitely Consider buying
1	2	3	4	5	6	7	8	9	10	11

This "full profile" approach is used in many studies because it is considered the most realistic representation of a consumers's actual buying process. The alternative "partial profile" approach describes concepts on only a subset of the full attribute list. While the full list in some sense represents reality, its use may render the rating or choice task too complex and confusing for consumers. By using partial profiles, the researcher gets a better understanding of the desired level and relative importance of secondary attributes. In the partial profile method, the attributes which are specified vary systematically from one judgment to the next so that in the end, the value system for the full set of attributes can be calibrated.
In addition to the content issue, the researcher also needs to decide on the presentation format. With the increasing use of electronic means to gather customer responses, the researcher may allow different alternatives to describe the product configuration. The existing body of literature indicates that product descriptions based entirely on words provide better predictive validity than pictorial presentation (Vriens, Loosschilder, Rosbergen and Wittink 1998). Most products tested thus far have been limited to those that require limited "styling" or design features. There is some evidence to indicate that prototype and computer animation can improve the predictive validity of a conjoint study (Dahan and Srinivasan 2000). It is possible that products with many attributes based on experience and / or emotion, can only be described in a limited way using words. Consequently, for such products verbal descriptors may not provide adequate predictive validity.

3.3.3 Respondent - Researcher Interaction format

Given the complexity of questioning, a majority of conjoint researchers prefer and gather conjoint data by personal interview mode. These are conducted either at a research facility, shopping mall intercept or at respondent's home. Another less popular but growing alternative is to use computer assisted interview modes. One important advantage of using computer interactive mode is to allow respondents to design and create their own list of attributes and attribute levels. Consider the product category like chocolate bar. There are more than forty brands on the market. A computer software could be used to create a list of brands that are relevant to respondent and use the list to create conjoint design. Recent advances in software and hardware, allow us to use computer interaction online or off-line or in-person using either desktop or notebook computers.

No doubt personal interviewing is expensive and hence many researcher often use mixed mode data collection to reduce costs. To understand mixed mode data collection, consider data collection operation consisting of three broad activities, initial contact, responding to instrument and communicating responses. In mixed mode data collection, these activities are accomplished by telephone, mail (both surface as well electronic), and facsimile which are usually cheaper to use than personal interviews. These alternatives, however, create problems relating to sampling, response rate, and response quality. Consequently, issues pertaining to sampling, response rate, response quality and cost of conducting research must be resolved to provide greater value of conjoint research.

3.3.4 Response Type

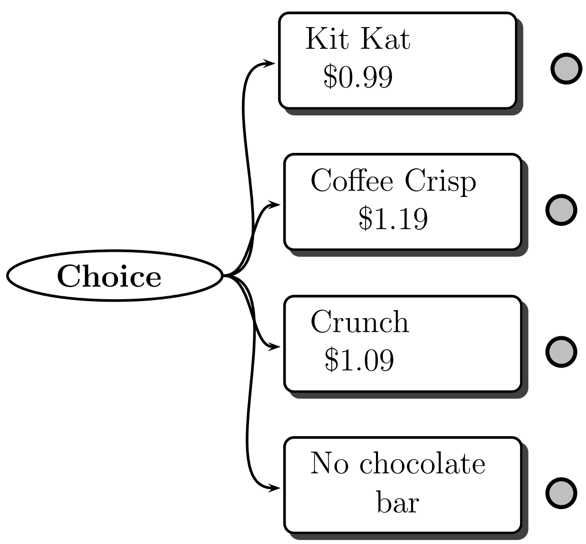
The fourth research design decision concerns the format in which respondents are asked to express their judgments, that is, ratings or ranks or choices. The "Made in the U.S.A." study noted above is a rating scale application, that is, without explicitly considering other options, customers were asked to state how likely they would consider purchasing an item.

In ranking methods, respondents are asked to compare a number of other options (see Appendix). Preferences are expressed in one of two ways: a "paired comparison" task or a top-to-bottom ranking. In paired comparisons, the respondent is presented with a number of pairs of products and is asked to choose one or the other. For example, execution of the "Made in the U.S.A." study in this format would replace the purchase likelihood rating with a series of questions (as described below).

The second type of ranking method is to rank order a set of concepts from most to least desirable. To facilitate this task, the respondent usually is first asked to sort the product descriptions into three piles, for example: *Like very much*, *Like moderately* and finally *Like little or not at all*. After the sorting is completed, the respondent is asked to rank within the piles. This produces the full ranking. Ranking n concepts is equivalent to making $\frac{n(n-1)}{2}$ paired comparisons, the number of distinct pairs which can be formed by taking two products at a time from a set of n items.

Which car would you consider buying?

	FORD		TOYOTA
Country of component manufacture	*USA*		*JAPAN*
Discount price off $17,000	*4%*		*9%*
Country of assembly	*USA*	OR	*MEXICO*
Driving distance to dealership	*10 minutes*		*10 minutes*
Dealership "reliability"	*Often requires a second visit*		*Get it right the first time*
Dealership "empathy"	*"One size fits all" approach*		*Personalized Attention*



The idea of the paired comparison is extended often to situation involving choice among more than two alternative. This format in the literature is called "discrete choice experiments". By including many more alternatives at a time, it may be possible to simulate a store or a customer choice environment. Furthermore, the researcher may also allow option to "opt-out" or "no choice" or "continue with current option". By including the opt-out option, it becomes possible to calibrate conditions that facilitate primary product category demand. Consider the following example involving three different chocolate bars; Kit Kat, Coffee Crisp and Crunch. It is likely that if a store only had three brands and all were priced high, some consumers may prefer to buy something other than a chocolate bar. To capture such buying behaviour, the opt-out option is a useful alternative. The following choice tree illustrates implementation of the opt-out option.

In many industrial and business-to-business transactions, customers may choose to buy from one or more vendors at the same time. This may be driven by the idea of a preferred vendor or to minimize supplier-related risks. To capture such decisions, one may ask respondents to allocate the share of purchase to a number of alternative suppliers with the constraint that the sum of all shares equal to 100.

Ranking and rating data generally produce very similar final results (Green and Srinivasan 1978). Traditionally, ranking methods were preferred because providing a quantitative measurement of the "degree of liking" or "degree of intention to buy" was felt to strain the capabilities of respondents. It is generally observed that full rankings often take four to five times as much time as one would to perform rating tasks. Consequently, Wittink and Cattin (1989) report that rating scales increased from 34% frequency of use in 1971-1980 to 49% in 1981-1985. The choice of method is largely situation-specific and relates to the form that a respondent is able to provide more reliable and / or valid responses.

3.3.5 Criterion

The next research decision involves the issue of the standard to be used in the judgments. The two major types of standards are, preference or likelihood / intention to purchase. This is not a trivial task since the answer to a choice between a Ford Mustang and Ford Focus depends upon the standard.

Ford Mustang 2-Seater Sports $35,000	OR	Ford Focus 4-Seater Sedan $20,000

Consider for example asking, *Which do you prefer?* versus *Which are you more likely to buy?* I may "prefer" the Mustang option (even if I am not paying $35,000). However, I don't have the $35,000 in the first place and it is likely that I will purchase the Focus.

These two different standards are used about equally in practice (Cattin and Wittink 1982). The choice depends largely on whether the focus of the study is market share or unit sales where the market size is to be estimated. If the latter, then intention to purchase is necessary to gauge the likely market size.

3.3.6 Methods of Data Analysis

The analysis depends on the previous decisions with respect to the input data collected. Most commonly, the following are used:

Form of judgment about alternatives	Data analysis
Rating Scores	Regression Analysis
Probability of Purchase	Logit Model
Rankings	MONANOVA or LINMAP
Choice	Multinominal Logit
Share Allocation	Share Model

If rating scores have been collected, for example, "indicate how much you like this product on a scale of 1 to 10," the value system is derived through regression analysis. If the respondent has expressed a probability of purchase, a logit model (an adaptation of regression) is used to accommodate the fact that probabilities are between 0 and 1. If ranks are used, it is appropriate to recognize that we really do not know by *how much* one alternative is preferred over another. We analyze only the ordering by a monotone analysis of variance (MANANOVA) or LINMAP or order logit model[2]. If responses are in the form of choices (pick one or more from many more

[2] Although it is mathematically true that rank ordered variables can not be used as dependent variable in regression analysis, empirical evidence by Cattin and Wittink (1979) suggest that ranks subjected to regression analysis, provide reasonable part-worth estimates.

alternatives), then one must use a multinomial logit model. Finally, if responses are in the form of share allocation decisions, the share models must be used to derive attribute importance as well as attribute level valuations or part-worths. A few examples are included in the attached appendix.

Each procedure yields an estimate of the value system of the respondent. For example, Jain et al. (1999) report the value system of cell phone users (on an average) with respect to choice of cell phone service. (we report only 3 of the 5 attributes here):

Monthly access charges		**Phone Price**		**Contract Term**	
$12.95	0.000	Free	0.000	1 year	0.000
$24.95	-0.921	$29.95	-1.174	2 years	-1.181
$44.95	-3.406	$69.95	-3.138	3 years	-1.864
$79.95	-5.677	$119.95	-3.142		

From this value system, one can obtain the value that consumers place on any new service package that service providers offer in the market place. This may provide us with a prediction about which packages might be preferred by consumers. (Note: the other attributes in the study were rate for additional minutes and service and network quality).

The following section more completely describes the type of ana lyses one can do with these data.

4 Analyzing the Outputs

In conjoint analysis, each individual provides a set of judgments and his / her value system is computed separately. There is no assumption that all consumers have the same value system. The three major types of analysis are:

1. Aggregate analysis of attribute importance and desirability.
2. Segmentation analysis.
3. Competitive scenario simulations to predict sales levels.

We will now discuss each.

4.1 Aggregate Analysis

Although one of the virtues of conjoint is its separate treatment of each individual, the most common first interpretation step is to compute average part worths of each attribute level across the entire sample of respondents to give the analyst an overall feeling for which attributes are generally important and what is the most desired level of each. Consider again the average value system for cell phone choices from previous page.

First, the scores indicate the relative desirability of alternative levels of each attribute. Not surprisingly, consumers prefer cell phones that have access charges of $12.95 per month, are free and require a one year contract term. Second, the difference among the scores for levels of a given attribute gives a rough measure of that attribute's importance. In general, the relative importance is proportional to the range covered by the levels. The monthly access charges has a range of 5.677 (0 minus −5.677), phone price has a range of 3.142 and contract term has a range of 1.864. Dividing each of these ranges by the sum of the three ranges gives a set of relative importance numbers which sum to one:

$$\begin{aligned}
\text{Monthly access charges} &= \frac{5.677}{5.677+3.142+1.864} = 53.1\% \\
\text{Phone price} &= \frac{3.142}{5.677+3.142+1.864} = 29.4\% \\
\text{Contract term} &= \frac{1.864}{5.677+3.142+1.864} = 17.4\%
\end{aligned}$$

This is a rough indicator of importance, because the percentages are dependent on the specific levels of the attribute used in the study. For example, suppose the monthly access charge attribute levels were: \$12.95, \$22.95, \$32.95, \$42.95 and \$52.95. This would decrease the importance of the monthly access charge attribute given this method of calculation because \$52.95 would not have a large negative utility that is associated with \$79.95. This must be kept in mind when interpreting the results. It is a good estimate of importance only if the variable levels specified cover the range of relevant options.

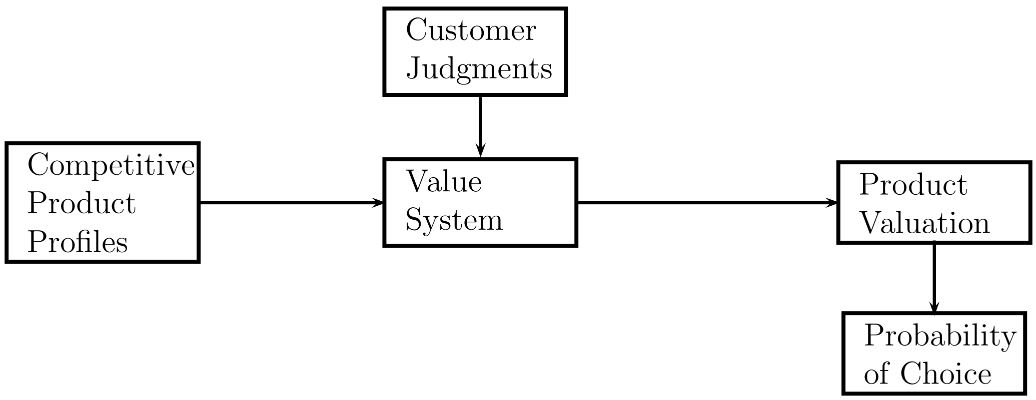
4.2 Segmentation Analysis

The averages are useful, convenient, and easy to understand summary measure. In most marketing situations, however, strategies are based on customer segments. There are number of alternative approaches to derive segments. Since the value system can be derived for each respondent, a cluster analysis can be used to produce "benefit segments". Idea behind clusters is to group respondent such that segments have similar within a segment and different across segments. Instead of cluster analysis one may use latent class approach to derive statistically meaningful segments. Another alternative is to look at predefined group of customers based on some prior knowledge about them. For example, current versus prospective customers or heavy versus light volume buyers.

Jain et al. (1999) performed segmentation analysis by looking at the preference pattern of cell phone user for personal or professional segments. Of the five attributes, the "personal" segment attached more importance to monthly access charges (45%) and phone price was the second most important attribute (25%). For the "professional" segment, rate for additional minutes was the most important attribute (27%) while phone price (25%) and contract term (23%) were the second and third most important attributes. Note that understanding this variation of attribute importance and desired levels across consumers is crucial for target market selection. An optimal package for the professional segment must focus on on-going costs (monthly charges and per minute charges) while for the personal segment these costs may not be that critical.

4.3 Scenario Simulations

The third major use of conjoint analysis is in predicting market shares or unit sales in various scenarios. Given the value system of a consumer and a description of alternative products, one can calculate the value of alternative products. These values permit the prediction of choice the consumer would make if confronted with these products in the market place.



The simulation process is shown in the above figure. Customer judgments are based on alternative products and these result in customer the value system. The value system then can be used to derive the value of *any* product (not just the ones originally used to derive the value system) which can be described by the set of attributes included in the analysis. Note that the value system captures customer preferences. These preferences may be unrelated to the competitive products available in the market place.
Consider an example of the notebook computer and, for the sake of simplicity, let's assume there are four attributes of importance: weight, battery life, quality of resolution of screen, and price. A standard conjoint analysis produces the following value system for an individual.

Weight		**Battery Life**		**Processor Speed**		**Price**	
$\leq$ 6 lbs	1.2	1 hour	0.0	400 MHz	0.0	$1,000	1.0
6 - 8 lbs	0.9	2 hours	0.2	600 Mhz	0.4	$2,000	0.5
$\geq$ 8 lbs	0.0	4 hours	1.5	800 MHz	0.5	$3,000	0.0
		8 hours	1.5				

Given a set of product descriptions on these attributes, one can calculate the value of each alternative and make a prediction about which system would be purchased. For example, if the three products available are:

Product	Weight	Battery Life	Processor	Price
A	6 lbs	1 hour	600 MHz	$2,000
B	7 lbs	4 hour	400 MHz	$1,000
C	9 lbs	8 hour	400 MHz	$1,000

We can calculate the value of each product as follows:

$$\begin{aligned}\text{Value of Product A} &= \text{Value of 6 lbs. weight}\\ &\quad +\text{Value of 1 hour battery life}\\ &\quad +\text{Value of 600 MHz processor speed}\\ &\quad +\text{Value of \$2,000 price}\\ &= 1.2 + 0 + 0.4 + 0.5 = 2.1\end{aligned}$$

Similarly, products B and C would have value of 3.4 and 2.5 respectively for this individual.

There are two major rules used to translate these values into choice predictions: the "first choice" rule and the "share of preference" rule. In the first choice rule, we simply say the person will buy the product that has the highest value. In this case, we predict this individual would purchase product B. Its low price, moderate weight and four-hour battery life more than make up for its disadvantage on processor speed compared to the other two products. We do this for each individual in the sample. A product's market share is simply the percentage of consumers for whom that product "wins", that is, has the highest value.

The second rule used is the "share of preference" rule which in effect gives a probability estimate that a consumer will buy a brand. For mathematical reasons[3], it may be necessary to compute share of exponentials. Such shares are often called in the marketing literature as share of attractions or utilities. In our example, the values and associated shares are shown below.

Example of Share Calculations

Product	Value	Share of Preference	Attraction	Share of Attraction
A	2.1	26.25%	8.17	16.24%
B	3.4	42.50%	29.96	59.55%
C	2.5	31.25%	12.18	24.21%
Sum	8.0	100.00%	50.31	100.00%

In the "share of preference" approach, probability that this individual will chose the "best" product B is $\frac{3.4}{8}$ =42.5%. The probability of choosing A or C is 26.25% (2.1/8) and 31.25% (2.5/8), respectively. The market share for a product is the average purchase probability across all customers in the study. The rationale behind the share of preference method is that consumers do not always buy their most preferred alternative. This is because store may be running out most preferred alternative or may not be available in the store at the time of purchase. Note that most preferred alternative approach tend to favour high share brands. On the other hand, share of attraction approach is a compromise between the two extremes, most preferred or share of value approaches. Commercial conjoint software packages offer the researcher the option of selecting between one of these three rules.

The scenario simulation capability is a powerful tool. For new products, one may be able assess product introduction strategy. Particularly, a prospective new product on the salient attributes, one can obtain not only a market share estimate, but also an indication of which competitive products will be hurt most. This is achieved by first simulating the scenario of only the current competitive products being available and then the environment of current competitive products plus the prospective new product. The scenario simulation also could be used to determine product profitability.

[3]It is possible that values associated with some attribute levels may be negative. In such situations, computing shares and probabilities may be difficult. Thus, it is useful to compute share of exponentials, which are always positive.

5 Accuracy of Conjoint Analysis

As noted in the introduction, conjoint analysis has been used for a wide variety of applications. Many firms are "repeat buyers" of the methodology, suggesting satisfaction with the accuracy of the results and their utility in managing a business. There is some evidence that supports internal and external validity of the conjoint results. Each product category and target customers are different. Therefore, it is important in an individual situation to be able to check the validity of the findings before implementing actions based on the derived value system. The three primary checks are: (i) common-sense test, or face validity (ii) holdout prediction, and (iii) actual vs. predicted market share. In the "common-sense" test, one simply asks if the results make sense given everything we know about the market place. For example, we may have a prior, strongly-held belief, that price is the most important attribute in a category. We may not be able to quantify this, but our experience with the category tells us it's the most important. If we conduct a conjoint analysis and price is not identified as key, we might want to investigate reasons for such observations. A second possible check of this type is to see if the parameter estimates vary across individuals in a reasonable way. Going back to our computer example, battery life is one of the key attributes. If we also collected data from students on whether or not they planned to use their PCs in four-hour examination situations, those who indicated "yes" would logically place more value on a battery with a four hour life expectancy than those who do not plan to use the computer in such a way. We could check to see if this holds up across our sample.

The second possible test is a holdout prediction. This is used in most of the studies that use conjoint analysis (Wind, Grashof and Goldhar 1978). In this test, a small number of the original products rated by the respondent are "held out" from the calculation of the value system. (Wind et al. held out 4 of 22 rated concepts.) Once the value system is computed, the value of all concepts (those held out and those not) is calculated. The test can be made if the value system-based calculations rate the held-out concepts correctly with respect to the other concepts. In their study, Wind et al. report 84% of the held-out concepts being correctly classified, "suggesting a high level of validity" (p. 36).

Finally, in some cases it is possible to simulate the current market situation and compare the market share estimates from the conjoint model with those observed in the market place. Also, if it is possible to observe what an individual respondent's "current brand" is, a check can be made to see if that brand has the highest value of all products currently available. This was the test used by Parker and Srinivasan (1976) in their study of rural health care facilities.

The ultimate test, of course, is whether the predicted results come true in the market place when certain actions are taken. There is limited evidence to suggest that conjoint predictions also hold in the market place. Moreover, the regular use of conjoint also suggests that it meets the market test on this dimension.

6 Guidelines for Use

The necessary assumptions underlying conjoint analysis have been discussed throughout this paper. We summarize main ideas here situations wherein conjoint analysis would be most applicable.

1. Product as a bundle of attributes.
   The product must be able to be specified as a collection of attributes. This is possible in most

instances where products and services are sold in the market place on routine basis. There are, however, some products where image or overall product perception drive customer valuation. This is particularly true for perfumes, wines and works of art.

2. Researcher must know important attributes.
   Conjoint analysis requires that we either know or determine attributes that are salient in the product category. There are many alternative perspectives about specifying important attributes and researchers should use them to construct product description without misleading respondents. Note that we may want to select five to seven attributes because respondents may have limitation in terms of processing provided product description.

3. Respondents can reasonably rate products.
   The input data we require from respondents are overall preference or purchase likelihood judgments. This requires a level of respondent familiarity with the products. In situations where respondents may be unfamiliar with new product concept, a prototype or a mock-up may be needed.

4. Attributes should be actionable.
   The firm should, in most cases, be able to act upon the output of the conjoint analysis by producing products which deliver the attribute levels used in the analysis.

5. Choice shares and price premiums are indicators.
   The conjoint analysis will provide insights about customer perception of price and value. Managers often think that estimated price premiums can be used to justify substantial price increase. Such decision behaviour in the market place, most probably will lead to substantial decrease in market share and profitability. In other words, conjoint study will suggest opportunities or threats to market share but manager must weigh risks associated changing prices in terms of profitability, market share and achieving sustaintable competitive advantage.

This note has provided the basic principles of conjoint analysis. Many researchers are currently at work expanding the domain of applicability and accuracy of conjoint analysis. For example, hybrid conjoint analysis merges the individual's own articulation of the value system with classic conjoint output. There is also growing interest in merging scanning data collection to conjoint based data collection to predict customer behaviour. No doubt these efforts are resulting in better results from conjoint and we expect to see increased application of conjoint-type methods in the future. While advanced versions of conjoint software are being developed, for many applications, easy-to-use PC-based systems (such as Sawtooth Software's ACA system) provide the necessary features.

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Conjoint Analysis: An Application to Orange Juice

SAS software can be used design and analyze conjoint based datasets. We will first indicate an approach to design conjoint data collection. Then, we will analyze collected dataset. Our dataset has slightly different design than one generated below.

• **Creating Conjoint Designs**

Designs that are used in conjoint analysis are based on either ranking or rating tasks or choice tasks. In most instances, we are mainly interested in the main effects designs. Assuming that we have made decisions about conjoint attributes, in designing conjoint study our interest lies with making decision about number of product combinations to be presented. In choice task, we also have to decide about number alternatives to be presented at a time. SAS software contains `PROC PLAN` and `PROC FACTEX` for generating alternative product combinations and `PROC OPTEX` procedure for making comparison of alternative designs. We can examine one possible approach to generate Orange juice alternative combinations. In this example, we had following attributes.

1. Brand (codes used in parenthesis)
   - Minute Maid (1)
   - Fairlee (2)
   - President's choice (3)
2. Method of Preparation
   - Fresh frozen (1)
   - From concentrate (2)
   - Pasteurized and frozen (3)
3. Package material
   - Glass jar (1)
   - Aluminum can (2)
   - Tetra-Pak (3)
4. Package price of \$0.60, \$0.80 or \$1.00.

Using `PROC PLAN` we can generate $3 \times 3 \times 3 \times 3 = 81$ combinations. These 81 combinations are then used by `PROC OPTEX` to generate design that contains 9 products that can be used to evaluate consumer preferences.

SAS Input

```
options ps=60 nocenter nodate;

proc plan ordered seed=46062;
   factors  price = 3
            brand = 3
            prep = 3
            pack = 3
            / noprint;
   output out=two  price  nvals=(60 80 100)
                   brand    nvals=(1 2 3)
                   prep   nvals=(1 2 3)
                   pack  nvals=(1 2 3)
;
run;
proc optex seed=27513 data=two;
   class brand prep pack price ;
   model brand prep pack price;
   blocks structure=(1)9 iter=10;
   output out=design;
run;
proc sort data=design; by brand; run;
proc print data=design; run;
```

SAS Output

```
Design     Treatment      Treatment
Number   D-efficiency   A-efficiency
-------------------------------------
     1      57.7350        50.0000
     2      57.7350        50.0000
     3      57.7350        50.0000
     4      57.7350        50.0000
     5      57.7350        50.0000
     6      57.7350        50.0000
     7      57.7350        50.0000
     8      49.8450        34.4828
     9      49.8450        34.4828
    10      47.1405        32.8767

OBS    BLOCK    BRAND    PREP    PACK    PRICE

 1       1        1        1       2      100
 2       1        1        2       1       60
 3       1        1        3       3       80
 4       1        2        3       2       60
 5       1        2        2       3      100
 6       1        2        1       1       80
 7       1        3        1       3       60
 8       1        3        2       2       80
 9       1        3        3       1      100
```

Note that SAS examined 10 different designs with various statistical criteria and suggested one such design that is balanced, each attribute level occurs equal number of times, and each attribute is independent of others. Since we have at most 8 parameter (2 for each attribute), nine alternative products is just enough to estimate those parameters. To generate choice based conjoint design, we would have to drop brand attribute and treat block as equivalent to brand attribute and change number of blocks as 3.

SAS Input

```
options ps=60 nocenter nodate;

proc plan ordered seed=46062;
   factors  price = 3
            prep = 3
            pack = 3
            / noprint;
   output out=two  price  nvals=(60 80 100)
                   prep   nvals=(1 2 3)
                   pack  nvals=(1 2 3)
;
run;
proc optex seed=27513 data=two;
   class prep pack price ;
   model prep pack price;
   blocks structure=(3)10 iter=10;
   output out=design;
run;
proc print data=design; run;
```

SAS Output

```
Design     Treatment      Treatment
Number   D-efficiency   A-efficiency
------------------------------------
     1      56.9210        50.2326
     2      56.9210        49.8462
     3      56.9210        49.4656
     4      56.9210        49.4656
     5      56.9210        49.0909
     6      56.9210        49.0909
     7      56.9210        48.7218
     8      56.9210        48.3582
     9      56.8819        48.2845
    10      56.7885        49.1933

OBS    BLOCK    PREP    PACK    PRICE

  1      1        2       2       80
  2      1        1       2       60
  3      1        1       3      100
  4      1        2       3      100
  5      1        3       3       60
  6      1        3       1       80
  7      1        3       1      100
  8      1        1       1       80
  9      1        2       2       80
 10      1        2       2       60

 11      2        2       3       80
 12      2        1       1      100
```

```
 13      2        1       3       80
 14      2        2       2       60
 15      2        2       1      100
 16      2        1       1       60
 17      2        3       3       80
 18      2        3       1       60
 19      2        1       2       80
 20      2        3       2      100

 21      3        1       3       60
 22      3        1       1       80
 23      3        2       1       80
 24      3        1       2      100
 25      3        3       3       60
 26      3        2       1       60
 27      3        3       2       80
 28      3        3       2      100
 29      3        1       2       60
 30      3        2       3      100
```

Another SAS procedure (`PROC FACTEX`) also can be used used to generate alternative designs. `FACTEX` requires that all attributes have equal number of levels while `PROC PLAN` does not require that. This may be a limitation of `FACTEX` procedure but it is also more efficient if you have 8 or 10 attributes each with 4 or more levels in generating a small subset of product designs.

- **Analyzing Conjoint Designs**

Suppose we collected ranking of 12 products from 9 respondents. Each respondent was asked to rank each package from *most likely to buy*(1) to *least likely to buy* (12). In choice experiment each respondent was asked to make 10 choices and each choice situation involved three alternative brands. Collected data is shown below. Note that the first column is used to identify respondent. Next 10 columns indicate particular brand chosen when faced with a particular choice occassion. Next 12 columns indicate ranking of 12 packages with the first column indicating package name that individual is most likely to buy. The last column identify each respondent who participated in the study.

```
 1 1 2 2 3 1 3 1 1 3 2 A L F C D J I G K E B H Melanie
 2 1 1 2 1 1 3 1 1 3 2 A D F E I J B L K C H G Wenli
 3 1 2 2 2 1 3 3 1 1 3 A F L K C D E J G H B I Brian
 4 1 1 1 3 1 1 2 3 3 2 L A G C K J D B I F E H Francis
 5 1 1 2 1 1 2 3 1 1 3 A K L E J H B G F D C I Diane
 6 1 2 2 2 1 3 1 1 3 2 A D I F J C L G B K E H John
 7 1 1 1 1 2 1 2 3 1 2 G H C F E I D B A L J K Vicki
 8 1 2 1 2 1 3 2 3 3 3 L K C A F G D E I H J B Alina
 9 2 2 2 1 1 3 3 1 1 3 K A L F E J C D H B G I Quang
```

SAS Input to Analyze Ranking Data

```
options nodate nocenter ps=70 ls=75;
```

```
data ojprof;                /*   Read Product Profiles   */
input situat brand prep pacmat price ;
datalines;
 1 1 1 1 0.60
 2 1 2 2 1.00
 3 1 3 3 0.80
 4 1 1 3 0.80
 5 2 1 2 0.80
 6 2 2 3 0.60
 7 2 3 1 1.00
 8 2 1 2 1.00
 9 3 1 3 1.00
10 3 2 1 0.80
11 3 3 1 0.60
12 3 3 1 0.60
;;;;
run;
data ojrank ;                  /*  Read Choices and Ranks     */
infile "c:\pricing\oj_clas.dat";
input id ch1-ch10
      A1 $ A2 $ A3 $ A4 $ A5 $ A6 $ A7 $ A8 $ A9 $ A10 $ A11 $ A12 $ Name $;
array rank(12) rank1-rank12;
array alpha(12) A1-A12;
retain rank1-rank12 .;        /*    Rank 12 means more likely to buy  */
   do i=1 to 12;
   if alpha(i) = "A" then rank(1) = 13 - i;
   if alpha(i) = "B" then rank(2) =13 - i;
   if alpha(i) = "C" then rank(3) =13 - i;
   if alpha(i) = "D" then rank(4) =13 - i;
   if alpha(i) = "E" then rank(5) =13 - i;
   if alpha(i) = "F" then rank(6) =13 - i;
   if alpha(i) = "G" then rank(7) =13 - i;
   if alpha(i) = "H" then rank(8) =13 - i;
   if alpha(i) = "I" then rank(9) =13 - i;
   if alpha(i) = "J" then rank(10) =13 - i;
   if alpha(i) = "K" then rank(11) =13 - i;
   if alpha(i) = "L" then rank(12) =13 - i;
end;
run;
                             /*    Transpose Choices,               */
                             /*    There will 12 Records per person  */
proc transpose data = ojrank
     out = res1(rename=(col1=rank) drop =_name_) ;
   by id;
   var rank1-rank12;
run;

data res2(drop=i situat);
i = mod(_n_ - 1,12) + 1;
situa = i;
set res1;
   set ojprof point=i;     /*    Read in choice profile information  */
   output ;
run;
                           /*     Compute Various dummy variables     */
data res3;
  set res2;
minute = 0;
fairlee = 0;
if brand = 1 then minute = 1;
if brand = 2 then fairlee = 1;
prep1 = 0;
```

```
prep2 = 0;
if prep = 1 then prep1 = 1;
if prep = 2 then prep2 = 1;
pacmat1 = 0;
pacmat2 = 0;
if pacmat = 1 then pacmat1 = 1;
if pacmat = 2 then pacmat2 = 1;
proc sort ; by id;
proc reg data=res3 ;
model rank = minute fairlee
          prep1 prep2 pacmat1 pacmat2 price ;
by id;
run;
```

A Summary of SAS Output

Id	Attribute Levels							R^2
	Minute Maid	Fairlee	Fresh frozen	Concen-trate	Glass jar	Alumi-num can	Price	
1	2.226	1.027	1.210	1.043	-0.044	-5.382	-9.100	0.800
2	1.202	-0.226	6.576	5.400	-0.453	-2.176	-10.565	0.882
3	2.521	2.497	-0.305	-0.678	0.438	-0.984	-19.592	0.991
4	3.076	-0.285	-2.471	-2.738	4.140	-1.578	0.120	0.934
5	-0.046	-0.549	1.358	0.048	6.092	6.451	-12.205	0.995
6	2.463	0.121	4.549	4.036	-0.114	-7.691	0.303	0.951
7	2.515	6.583	-1.557	-2.345	-2.384	-3.063	8.958	0.950
8	0.682	0.957	-3.619	-5.742	-0.996	-1.411	-13.442	0.975
9	-0.192	-0.305	-0.072	-0.425	1.307	2.772	-21.596	0.977
Mean	1.605	1.091	0.630	-0.156	0.887	-1.451	-8.569	0.939
t-stat	2.037	1.314	0.801	-0.187	1.124	-1.634	-4.127	0.301
t-prob	0.044	0.192	0.425	0.852	0.264	0.105	0.000	

President's Choice, Pasteurized and frozen and Tetra-pak
are used as base conditions for respective attributes

If we use R^2 as a measure of goodness-of-fit between observed ranks and predicted ranks, we note that there is good correspondence and in some instances our model predict ranks very well. We also could conclude that models proposed here capture individual differences very well. Moreover, some individuals appear to focus on one attribute (for example, individual 9 has focussed on price alone) while others have focussed their attention on more than one attribute (for example, individual 1 has focussed on brand and package material). We turn our attention to estimating choice model.

SAS Input for Analyzing Choices

```
options nocenter nodate ps=65 ls=75;
data ojprof;                /*   Read Choice Profiles   */
```

```
infile "c:\pricing\ojch1.prn";
input situat brand prep pacmat price order;
datalines;
 1 1 1 1 0.60 1
 1 2 1 2 0.60 2
 1 3 1 1 0.60 3

 2 1 2 2 1.00 3
 2 2 3 3 0.60 2
 2 3 2 2 1.00 1

 3 1 3 3 0.80 3
 3 2 2 1 0.60 1
 3 3 3 3 0.80 2

 4 1 1 2 0.80 1
 4 2 3 1 0.80 3
 4 3 3 1 0.80 2

 5 1 2 3 0.60 2
 5 2 2 3 0.80 1
 5 3 2 2 1.00 3

 6 1 1 3 1.00 3
 6 2 1 2 0.80 2
 6 3 1 3 0.60 1

 7 1 1 3 1.00 2
 7 2 3 1 1.00 1
 7 3 2 1 0.60 3

 8 1 2 1 0.80 1
 8 2 1 3 1.00 3
 8 3 3 3 1.00 2

 9 1 3 2 0.80 3
 9 2 1 2 1.00 2
 9 3 1 1 0.60 1

10 1 2 2 1.00 2
10 2 1 1 0.80 1
10 3 3 2 0.60 3
run;
data ojch ;                   /*  Read Choices           */
infile "c:\pricing\oj_clas.dat";
input id ch1-ch10
      A1 $ A2 $ A3 $ A4 $ A5 $ A6 $ A7 $ A8 $ A9 $ A10 $ A11 $ A12 $ Name $;
run;
                             /*    Transpose Choices,               */
                             /*    There will 10 Records per person  */
proc transpose data = ojch
     out = res1(rename=(col1=ch) drop =_name_) ;
   by id;
   var ch1-ch10;
run;
                             /*   Convert Choice observations 1 or 2  */
data res2(drop=ch situat);
i = mod(_n_ - 1,10) + 1;
situa = i;
set res1;
   do j = 1 to 3;
   choice = 2 - (j eq ch);
```

```
   ij = (i - 1)*3 + j;
   set ojprof point=ij;     /*    Read in choice profile information  */
   output ;
end ;
run;
                           /*     Compute Various dummy variables     */
data res3;
  set res2;
minute = 0;
fairlee = 0;
if brand = 1 then minute = 1;
if brand = 2 then fairlee = 1;
prep1 = 0;
prep2 = 0;
if prep = 1 then prep1 = 1;
if prep = 2 then prep2 = 1;
pacmat1 = 0;
pacmat2 = 0;
if pacmat = 1 then pacmat1 = 1;
if pacmat = 2 then pacmat2 = 1;
proc sort ; by id;
proc phreg data=res3 outest = betas nosummary;
model
choice*choice(2) = minute fairlee
                   prep1 prep2 pacmat1 pacmat2 price  / ties = breslow;
strata id situa;
run;
```

SAS Output

```
The PHREG Procedure

Data Set: WORK.RES3
Dependent Variable: CHOICE
Censoring Variable: CHOICE
Censoring Value(s): 2
Ties Handling: BRESLOW

                 Testing Global Null Hypothesis: BETA=0

               Without       With
Criterion    Covariates    Covariates    Model Chi-Square

-2 LOG L        197.750       150.512      47.238 with 7 DF (p=0.0001)
Score              .             .         43.386 with 7 DF (p=0.0001)
Wald               .             .         31.158 with 7 DF (p=0.0001)

                Analysis of Maximum Likelihood Estimates

                 Parameter    Standard     Wald        Pr >
Variable  DF      Estimate      Error   Chi-Square  Chi-Square

MINUTE     1      1.471557     0.36040    16.67207      0.0001  Minute Maid
FAIRLEE    1      0.194885     0.37066     0.27645      0.5990  Fairlee
PREP1      1     -0.011471     0.35775     0.00103      0.9744  Fresh Frozen
PREP2      1     -0.955293     0.60693     2.47738      0.1155  From Concentrate
PACMAT1    1      1.175472     0.63943     3.37939      0.0660  Glass jar
PACMAT2    1      0.213025     0.57521     0.13715      0.7111  Aluminium can
PRICE      1     -4.482758     1.05526    18.04548      0.0001  Price of serving
```

- **Interpretation of Results**

Because multinominal logit model is non-linear, interpretation of estimated parameters requires more efforts than a linear models. We will use estimated model to interpret brand constants, own and cross-price elasticities, brand and attribute premiums as well as attribute importance. Suppose that utility or attraction for Minute Maid can be written as $V_m = \exp(a_m + b_1 \text{Price}_m)$ where a_m is brand constant for Minute Maid and b_1 is price coefficient. Similarly attraction of Fairlee and President's Choice are $V_f = \exp(a_f + b_1\text{Price}_f)$ and $V_p = \exp(b_1\text{Price}_p)$ respectively. Note that in this particular situation President's Choice is considered to be the base brand and its brand constant is assumed to zero. Then according to multinomial logit model, we may write

$$\text{Prob}_m = \frac{V_m}{V_m + V_f + V_p}.$$

You may write this as

$$\text{Prob}_m = \frac{\exp(a_m + b_1\text{Price}_m)}{\exp(a_m + b_1\text{Price}_m) + \exp(a_f + b_1\text{Price}_f) + \exp(b_1\text{Price}_p)}$$

If prices of three brands are identical, then above expression can be simplified to

$$\text{Prob}_m = \frac{\exp(a_m)}{\exp(a_m) + \exp(a_f) + \exp(0)}$$

or

$$\text{Prob}_m = \frac{\exp(a_m)}{1 + \exp(a_m) + \exp(a_m)}$$

In our example, Minute Maid brand has constant parameter of $a_m = 1.472$ and Fairlee brand has constant parameter of $a_f = 0.195$. This would imply that Minute Maid would have choice proportion of

$$\begin{aligned}
\text{Prob}_m &= \frac{\exp(1.472)}{1 + \exp(1.472) + \exp(0.195)} \\
&= \frac{4.358}{1 + 4.358 + 1.215} \\
&= 0.6629
\end{aligned}$$

Similar calculation for Fairlee would result in choice proportion of 0.1849 and for President's Choice to be 0.1522.

- **Deriving Own and Cross Elasticities**

To obtain own price elasticity[4] for the first brand, we need to obtain the partial derivative of this expression with respect to the first price. That is,

[4]Own price elasticity is percent change in choice share as a result of one percent change in own price. On the other hand, cross price elasticity is percent change in choice share of brand 1 as result of one percent change

$$\frac{\partial \text{Prob}_m}{\partial \text{Price}_1} = \frac{b_1 V_m}{V_m + V_f + V_p} - \frac{(V_m)^2 b_1}{(V_m + V_f + V_p)^2}$$

Note that above expression can be reduced to

$$\frac{\partial \text{Prob}_m}{\partial \text{Price}_m} = b_1 \text{Prob}_m (1 - \text{Prob}_m).$$

To get own price elasticity (η_{mm}), then we multiply both sides of above equation by $\text{Price}_m/\text{Prob}_m$, or

$$\eta_{mm} = (1 - \text{Prob}_m) b_1 \text{Price}_m.$$

A similar approach also can be used to derive cross price elasticity or the percent change in probability of choice for Minute Maid, as result of 1% change in price of Fairlee. If you do all above steps, we would get

$$\eta_{mf} = -b_1 \text{Prob}_f \text{Price}_f.$$

Consider a situation where all three brands are priced at \$0.85, then own and cross price elasticities would be

$$\boldsymbol{\eta} = \begin{pmatrix} -1.284 & 0.705 & 0.580 \\ 2.526 & -3.106 & 0.580 \\ 2.526 & 0.705 & -3.230 \end{pmatrix}$$

From this example, we would conclude that Minute maid has low own price elasticity and other two brands have relatively high own price elasticity. When price of Minute Maid is lowered, note that there is big shift in changes in probability that an individual would choose Fairlee and / or President's Choice. This is because Fairlee and President's Choice have high cross elasticities with respect to changes in Minute Maid prices. Intuitively, if Minute Maid lowers price, more of Fairlee and President's Choice buyers will switch away from them. On the other hand, if Fairlee lowers price, impact on Minute Maid is relatively small. This is because cross price elasticity is small.

Deriving Brand Price Premiums

One managerial question that is often asked with choice model is price premium associated with branded products. That is, holding everything else (product formulation, packaging and distribution) how much discount should Fairlee brand offer in order to get same share as Minute Maid brand? To answer this question, we would need to equate brand utility of two brands and solve resulting equation for prices. That is,

$$\begin{aligned} V_m &= V_f \quad \text{which implies that} \\ \exp(a_m + b_1 \text{Price}_m) &= \exp(a_f + b_1 \text{Price}_f) \quad \text{or} \\ \text{Price}_m - \text{Price}_f &= \frac{a_f - a_m}{b_1} \end{aligned}$$

change in price of brand 2 or brand 3. We would expect that own price elasticity to be negative and the cross price elasticities to be positive for substitute products.

Note that we would generally expect that b_1 to be less than zero. This would imply that if a_f is less than a_m (these are parameters associated with brands), the difference between two prices will be positive. In this case we would conclude that the second brand, Fairlee should lower its price to get same choice shares as the first brand. Note that the right hand side in the above expression is equal to \$0.285 which means that Fairlee should reduce its price to \$0.56 to get about 66% choice share. On the other hand, if a_f is greater than a_m, we would expect that the second brand could increase its price to keep same choice shares.
If two brands have differing prices, then one may want to compute the relative price premium by dividing both sides of above expression by Price_1. This would result in expression,

$$\frac{\text{Price}_m - \text{Price}_f}{\text{Price}_m} = \frac{a_f - a_m}{b_1 \text{Price}_m}$$

and can be interpreted as a percent premium (discount) over another brand. At price of \$0.85 Minute Maid could get 33.5% premium over Fairlee brand. Note that if Minute Maid price would have been lower than \$0.85 (say \$0.80), then price premium would be higher (at price of \$0.80 premium would be 35.61%).

Deriving Price Premiums for Product Attributes

Some product features are preferred by consumers while other features may be less valued. Moreover, to quantify and assign price premium associated with product features, expression for relative price premium may be used. This price premium amount often is termed respondents' are willingness to pay for brand or product feature. For example, in Orange juice example, coefficient for *packaging material* glass has estimate of 1.175 and that for alumnium can is 0.213. In this situation, third packaging material, tetra-pak is assumed to be zero. Suppose President's Choice is considering glass as packaging material instead of tetra-pak, and tetra-pak is priced at the base price of \$0.80. To determine, discount amount tetra-pak should offer in order to get same share as glass packaging, we need to equate utilities and solve for prices as it is done above. This would result in relative price premium for glass to be

$$\begin{aligned} \text{Glass Premium} &= -\frac{\text{Estimate for Glass}}{\text{Price} \times \text{Price Coefficient}} \\ &= -\frac{1.175}{0.8 \times -4.483} \\ &= 0.3276 \end{aligned}$$

In words, glass packaging material thus may get 32.76% price premimum over tetra-pak. Similar calculations for alumnium can would have price premium of 5.4%. Note that in this example tetra-pak gets zero percent or no price premium. Tables provide summary for all design attributes and willingness to pay for them. Note that negative price premiums imply that price discount may be needed to keep utility at the same level. In addition, price premiums are always relative to some other product feature and changing the base feature (one that has zero premium) does not alter relative price premiums. Finally, to compute overall price premium

Attribute Levels and Their Price Premiums

Attribute Descriptor	Utility	Price Premium
Brand		
Minute Maid	1.472	41.03%
Fairlee	0.195	5.43%
President's Choice	0.000	0.00%
Packaging Material		
Glass	1.175	32.78%
Aluminum can	0.213	5.94%
Tetra-pak	0.000	0.00%
Preparation		
Fresh Frozen	-0.011	-0.32%
From Concentrate	-0.955	-26.64%
Pastuerized	0.000	0.00%

Relative Importance of Attributes

Attribute	Minimum Utility	Maximum Utility	Range	Relative Importance
Brand	0.000	1.472	1.472	27.27%
Packaging	0.000	1.175	1.175	21.79%
Preparation	-0.955	0.000	0.955	17.71%
Price†	-4.483	-2.690	1.793	33.23%
Total			5.395	

† Because the maximum price in this situation is \$1.00 and the minimum price is \$0.60, to obtain minimum and maximum utility, multiply price coefficient by these prices

for a brand with variety of features, one may add all price premiums to determine overall valuation of new or revised brand. For example, if Minute Maid (premium of 41.03%)is available in glass (premium of 32.78%), and prepared from fresh frozen (discount of 0.32%), then these respondents will be willing to pay 73.49% price premium over President's Choice juice sold in tetra-pak and prepared using pasteurizing.