A Market-Oriented Approach to Maximizing Product Benefits: Cases in U.S. Forest Products Industries

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Conjoint analysis, a decompositional customer preference modelling technique, has seen little application to forest products. However, the technique provides useful information for marketing decisions by quantifying consumer preference functions for multiattribute product alternatives. The results of a conjoint analysis include the contribution of each attribute and attribute level to overall product utility, the relative importance of product attributes, and market share estimates for hypothetical product attribute combinations. In this paper, the technique is first examined by discussing the series of steps involved in a conjoint study. Following this, the application of conjoint analysis in two studies of forest products is demonstrated.

Introduction

Consider the following situation: You are a producer of softwood lumber and a competing company has made a decision to provide wane free lumber and to increase the grading accuracy of its lumber. How should you respond?

Perhaps you are a supplier of repaired pallets and your customers are asking for a better quality product. However, you are not certain how to obtain the greatest increase in quality for the cost. You might eliminate stringer repairs or tighten your restrictions on deckboard splits. Will this increase quality as perceived by your customers?

When faced with such problems, market-oriented companies will strive to understand the impact that product changes have on customer perceived quality. In other words, they will seek to understand customer preference structure and provide products which match these preferences. Much of the information available concerning customer preferences will be qualitative. However, companies may wish to supplement such information with the results of quantitative studies.

This paper describes one approach to obtaining and analyzing quantitative data concerning customer preference structures: conjoint analysis. We begin with a brief overview of preference models and a description of how conjoint analysis differs from alternative techniques. Conjoint analysis involves specific steps, each involving methodo-

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logical choices. These steps and choices are reviewed in the next segment of the paper. Finally, redescribe the application of conjoint techniques in two studies of forest products: softwood lumber used by manufacturers of preservatively treated products and repaired wood pallets used by the U.S. grocery distribution industry.

The primary purpose of this paper is to provide the marketing researcher in the area of forest products with a non-technical discussion of evolution of conjoint analysis and the various paths that marketing researchers have taken to multiattribute utility measurement. The paper is not meant to provide a comprehensive discussion or "how-to" of conjoint analysis. Rather it is meant to stimulate interest in this powerful tool.

BACKGROUND

PREFERENCE MODELS

There are two basic approaches to modeling buyer preferences: *compositional* and *decompositional* models. In compositional models, the total utility or preference for a product is estimated from evaluative data on individual attributes. In other words, this model begins with a set of explicit perceptions or beliefs about product attributes and uses them as a basis for predicting *overall* product evaluations (Holbrook 198 1). The value expectancy model (Fishbein 1967) and linear compensatory attitude model (Wilkie & Pessemier 1973) fall within this category.

When using decompositional models, utilities for individual attribute levels are estimated from data which describes *overall* customer evaluations of products. These models start with preference judgments for attribute bundles (i.e., products consisting of specific combinations of attributes and attribute levels) and use these judgments to infer the values associated with underlying attributes (Holbrook 1981). Conjoint analysis (Green & Rao 1971) is a decompositional model.

Although buyer preference models developed using compositional techniques provide an understanding of customer attitudes toward particular product attributes, they usually do not explain how buyers make trade-offs between the features (attributes) and price when bundled together within products. Interdependencies among attributes are not entirely explained by research techniques which examine each attribute independently. In reality, buyers do not purchase individual product attributes. Instead, buyers most often choose one product from several alternative products (bundles of attributes) based on the entire product and the ability of that product to satisfy their needs better than the available alternative products. Conjoint analysis (a decompositional model) can be used to understand the trade-off approach to product choice.

CONJOINT ANALYSIS

Conjoint analysis[1] is a measurement technique developed in the field of mathematical psychology by Lute and Tukey (1964) and introduced into marketing research by Green and Rao (1971). Since its introduction in the early 1970s, conjoint analysis has emerged as the most widely applied marketing tool for measuring buyer preferences among multiattribute alternatives and determining the trade-offs consumers make among multiattribute

[1] Conjoint analysis is sometimes called trade-off analysis since this procedure is concerned with trade-off judgments.

products. According to Wittink and Cattin (1989), commercial applications of conjoint analysis from 1971 to 1981 and from 1981 to 1985 were 698 and 1062, respectively. Most commercial applications of conjoint analysis were in new product concept identification, competitive analysis, pricing, segmentation, and product repositioning (Kohli & Mahajan 1991).

In conjoint analysis, overall judgments of a set of alternatives are decomposed into separate and compatible utility scores from which the original judgments can be reconstituted. The resulting information describes the relative importance of the product attributes and the value (utility) of the levels of each attribute. In other words, conjoint analysis provides a quantitative estimate of how each attribute level impacts a buyer's judgment (i.e., purchase decision).

The word "conjoint" is used because the relative values of attributes *considered jointly* can be determined even though they might not be measurable if taken one at a time (Churchill 1991). In conjoint analysis, the characteristics (key dimensions) of a product are described in terms of ***attributes.*** Variations within an attribute are described as levels. For example, exterior color of an automobile is an attribute, and the alternative colors (e.g., red, white, green) are levels of the color attribute. In other types of analyses, attributes are commonly known as independent variables and attribute levels are the values of the independent variables.

A researcher must follow certain steps in conducting a conjoint study. The following sections focus on the steps involved in conjoint analysis and the alternative available at each step.

Selection of Attributes

The first step in a conjoint study is the selection of product attributes and attribute levels. This selection should be done carefully since failure to include the appropriate attributes will result in a spurious model. Obviously, all attributes that are relevant to the consumer when selecting a product should be included (within the limitations described in the following sections), and all attributes that are not relevant to the purchase decision should be excluded. In practice, identifying the relevant attributes can be a significant task. Possible approaches include: carefully reviewing the previous studies that have investigated the same or similar products, interviewing people familiar with the product, using focus-groups of customers, and/or conducting a pilot study. A difficult and often subjective task is the reduction of the number of attributes to a level which is manageable yet sufficiently accounts for buyer preferences (Green & Srinivasan 1978).

Preference Models

The next step in conjoint analysis involves choosing a suitable preference model for the study. There are three preference models in common use, each of which differs in terms of the shape of the function relating attribute values to preference structure. The *vector*, *ideal-point*, and *part-worth* models treat values of each attribute as linear, linear plus quadratic (curvilinear), and piecewise linear, respectively. It is possible for a researcher to specify a mixed model in which some attributes follow the part-worth function model while other attributes follow vector and/or ideal point models (Green & Srinivasan 1990).

In general, the vector or ideal-point models should be specified for attributes whose values are metric (i.e., continuous). For example, the vector model would be appropriate for price (where the utility of a product could be theorized to decrease in proportion to a price increase). The ideal-point model is appropriate when a customer's preference for a product diminishes as the attribute levels reach extreme values. In this situation, customer preference for a product will be high when the attribute level value is closer to the ideal point. For example, some people prefer moderate levels of sweetness in coffee, and preference will decrease when sweetness decreases or increases from the moderate level.

The part-worth model is specified when attribute measurement is nonmetric. This model allows different preference function shapes along each of the attributes (Green & Srinivasan 1978). This model also allows the estimation of a part-worth or utility value for each level of each attribute. The general forms of the three models are described below:

First, let

U_{jn} = the total utility (preference) of the j^{th} stimulus for the n^{th} respondent

i = 1, 2, . . . , t denote the set of t attributes or factors that have been chosen

V_i = vector coefficient for the attribute i

X_{jn} = the level of the i^{th} attribute for the j^{th} stimulus facing n^{th} respondent

P_i = ideal-point coefficient for the attribute i

f_i = the function denoting the part-worth of different levels of X_{jni} for the i^{th} attribute

t = total number of attributes

Vector model

$$U_{jn} = \sum_{i=1}^{t} V_i X_{jni} \quad (1)$$

Ideal-point model:

$$U_{jn} = \sum_{i=1}^{t} [V_i X_{jni} + P_i (X_{jni})^2] \quad (2)$$

Part-worth model:

$$U_{jn} = \sum_{i=1}^{t} f_i (X_{jni}) \quad (3)$$

Conjoint Designs

The next step in conjoint analysis is the selection of a design for the collection of data. There are four main conjoint designs through which data can be gathered: (1) the pairwise trade-off method; (2) the full profile method; (3) the hybrid method; and (4) adaptive conjoint analysis.

Pairwise trade-off designs

The pairwise trade-off method gathers data on a two attributes-at-a-time basis. The respondent is asked to rank each pair of attributes at different levels from the most preferred to the least preferred (Green & Srinivasan 1978). This conjoint design method is simple and easy to apply while reducing potential information overload on the part of the respondent. However, by decomposing the product attributes into two-at-a-time combinations, this model sacrifices some realism. In addition, respondents may be unclear as to what should be assumed about the other attributes that are not shown in the two-attribute trade-off matrix. When the attributes of a product correlate, it is unclear what the obtained data really mean. In particular, a problem arises when one of the attributes presented in the stimulus is corre-

lated with other relevant attributes not included in the trade-off matrix. Perhaps because of these limitations, the use of the trade-off conjoint design method has decreased substantially (Wittink & Cattin 1989). According to Johnson (1987, p. 257), the tradeoff method ". . . *has become nearly obsolete."*

Full-profile designs

In contrast to the pairwise trade-off design, the full-profile design utilizes several attributes of a product at a time. In this method, a set of full-profiles are constructed where each profile consists of a certain combination of attribute levels (one per attribute). The respondent evaluates the set of full-profiles (also called stimuli) and ranks or rates each profile in terms of preference. The full-profile method is an improvement over the trade-off method because it provides more realistic descriptions of stimuli. The full-profile conjoint design was used in almost two thirds of the commercial studies conducted between 1981 and 1985 (Wittink & Cattin 1989).

The use of a full-profile design becomes problematic when the number of attributes and/or the number of levels of each attribute becomes large. For example, if there are six attributes with three levels each, the number of possible combinations a respondent might be required to evaluate will be 729 (3^6). This would undoubtedly cause information overload and may tempt respondents to simplify the experimental task by ignoring variations in the less important attributes or by simplifying the attribute levels themselves (Green & Srinivasan 1978). As a result, most conjoint studies rely on some type of fractional factorial design. The primary purpose of this design is to reduce the number of evaluations required of respondents. The fractional factorial design selects a subset of all possible combinations which still allows estimation of model parameters (part-worths or utilities) for all main effects without sacrificing the predictive power contained in the original design.

The full-profile method is generally limited to small number of attributes (usually no more than seven) in any specific experiment. Researchers should incorporate "bridging" factors in studies that require a larger number of attributes (Bretton-Clark 1992, Green & Srinivasan 1978). In bridging, the full set of attributes are first split into subsets of five or six attributes each. Each stimulus (card) is then composed of attribute combinations that involve those five or six attributes. In each subset one or two attributes are common to provide a basis for linking part-worth functions across the various subsets of attributes (Green & Srinivasan 1978).

Hybrid conjoint designs

Hybrid conjoint designs were developed to reduce the complexity of the data collection task in conjoint analysis while retaining the individual differences in preference (utility) estimation. There are two steps in hybrid conjoint analysis: (1) self-explicated data; and (2) traditional fill-profile stimuli rating.

The self-explication approach is a compositional technique similar to expectancy-value models of attitude theory (Wilkie & Pessemier 1973). While using this approach, the respondent first evaluates the levels of each attribute on a numeric scale (e.g., 0 to 10 desirability scale with the value of 10 for the most desirable level and 0 for the least desirable level). In addition, the respondent allocates 100 points among all attributes so as to reflect his/her

desirability ratings. The part-worth of each attribute level is calculated by multiplying the importance weights with attribute-level desirability, and the respondents overall preference for a given alternative is then calculated using the additive model (Green 1984).

$$U_j = \sum_{i=1}^{t} W_i U_{Ki} \qquad \textbf{(4)}$$

Where

U_j = the total utility (preference) of alternative (stimulus) *j*

W_i = the self-explicated importance weight for attribute *i*

U_{ki} = the desirability score for level *k* of attribute *i*

In the second step of hybrid conjoint analysis (i.e., traditional full-profile stimuli rating), each respondent provides evaluations of a limited number of profiles. A small number of profiles are drawn from a master full-profile design in a manner that permits orthogonal estimation of all main effects and selected t we-way interactions. The profiles are selected in such a way that each stimulus in the larger set is evaluated by a subset of the respondents. The hybrid part-worths are estimated through multiple regression by relating the overall preference judgments for the full profiles to the self-explicated utilities (Green 1984).

Adaptive conjoint analysis designs

Adaptive conjoint analysis (ACA) was developed by Richard Johnson at Sawtooth Software, Inc., Evanston, IL. The technique involves collecting preference data using microcomputers while customizing the stimuli presentations according to a respondent's prior evaluation of attributes and levels of attributes. It incorporates some of the strengths of both trade-off and full-profile approaches (Johnson 1987).

Green and Srinivasan (1990) suggest that the full-profile method should be preferred as a data collection tool when the number of attributes included in the study is six or less. They recommend the use of the trade-off method or bridging technique (if respondents are willing to do multiple card sorts) if the number of attributes is larger. They suggest the use of the self-explication approach or the combination methods such as Hybrid or ACA when the number of attributes is 10 or more. Indeed, Wittink, Vriens, and Burhenne (1994) report an increase in the application frequency of ACA as the number of attributes increases.

Stimulus Presentation

The next step in conjoint analysis is to select the method of presenting stimuli to respondents. The following are the primary presentation methods: (1) verbal description or profile cards; (2) paragraph description; (3) pictorial representation; (4) actual product or prototype product. In the verbal description (profile cards) approach, the respondent is presented with a number of stimuli with concise attribute level descriptions. This is, by far, the most widely used approach to presenting stimuli (Green & Srinivasan 1990, Wittink et al. 1994). In the paragraph description approach a more complete description of the stimulus is provided. The disadvantage of this method is that it limits the number of descriptions that can be presented, possibly making the estimated parameters less accurate (Green & Srinivasan 1978).

Pictorial representation using various kinds of visual props or three dimensional models is increasing in popularity (Green & Srinivasan 1990,

Wittink et al. 1994). This method conveys information in less ambiguous ways, reduces information overload by relieving respondents of the reading task and the need to visualize a large amount of information, makes stimuli more realistic, and makes the task interesting for respondents (Green & Srinivasan 1978). The major disadvantage of this method is cost and the possibility of a picture displaying the information in a way that differs from the researcher's intention. In a limited number of studies actual products or product prototypes were used as a stimuli (Green & Srinivasan 1990, Wittink et al. 1994). This method has all the advantages and disadvantages of pictorial representations.

Measurement Scale for the Dependent Variable

Once the stimulus presentation method has been selected, the researcher must choose the measurement scale for the dependent variable. The two types of scales commonly used are ranking and rating. The rating scale is the most popular measurement scale used in conjoint studies (Wittink & Cattin 1989, Wittink et al. 1994) and has the advantage of being easily implemented in mailed questionnaires. Depending on the purpose of the study, both types of scales can be used to measure either preference for a product or intention to purchase. A third scale type that is gaining popularity is graded paired comparisons in ACA (Green & Srinivasan 1990). In this method, respondents rate preference for profiles shown two at a time.

Estimation Procedures

Depending on the type of data collected, one of the following three procedures can be used to estimate the preference values (utilities or part-worths) of attribute levels: MONANOVA (Kruskal 1965), LINMAP (Shocker & Srinivasan 1977), and OLS regression. Initially, researchers favored non-metric estimation procedures (MONANOVA and LINMAP) for rank order data. However, Green and Srinivasan (1978) have shown that OLS applied to rank order data provides results comparable to non-metric procedures. Because of its simplicity and availability, OLS is widely used to derive utilities (Wittink et al. 1994; Wittink & Cattin 1989). Darmon and Rouzies (1991) report that OLS yields the least distorted weights when compared to other methods (i.e., LINMAP, MONANOVA) irrespective of the type of stimulus presentation used while collecting data. In addition, under fractional factorial design, OLS is by far the most preferable procedure as far as attribute importance weight estimates are concerned (Cattin & Bliemel 1978; Darmon & Rouzies 1991; Green & Srinivasan 1978).

Simulations and Sensitivity Analysis

Since conjoint analysis uses models developed at the individual respondent level, simulations and sensitivity analyses can be conducted. Simulation algorithms use a matrix of individual level utilities and a set of user-specified product profiles as inputs and provide the proportion of choices received by each product (i.e., its market share) as output. Using these algorithms, one can perform sensitivity analysis by examining systematically the interplay of utilities and product profiles. Most choice simulators currently available utilize a matrix of respondent background characteristics, such as the product currently

used and demographics, in addition to a matrix of respondent utility scores and a set of product descriptions (Green & Krieger 1988).

Simulation algorithms use one of three rules, *max-utiliy, share of utility (BTL), and Logit.* [2] However, the max-utility rule (which assumes that buyers choose the product with the highest utility) has been widely used in market research. Basic sensitivity analyses algorithms typically assume a max-utility choice rule (Green & Kreiger 1993).

CONJOINT STUDIES IN U.S. FOREST PRODUCTS INDUSTRIES

SITUATIONAL CONTEXT OF THE STUDIES

Study 1: Softwood Lumber

Softwood lumber producers maintain lumber quality by adhering to voluntary lumber grading rules. These grading rules provide a common method for maintaining certain quality characteristics and for conducting marketing activities. However, they provide little (if any) incentive for lumber suppliers to enhance the minimum required quality level. Since lumber grading rules allow variation within each grading category, suppliers may maximize these variations to increase lumber recovery. As a result of this concentration on lumber recovery, mills may produce lumber that barely passes the minimum standards set by the grading rules. A lumber recovery orientation is further encouraged by raw material costs which can account for 60 to 80% of the total cost of lumber production.

[2] See Green and Krieger (1988) for further information about these choice-rules.

Most softwood lumber grading rules are based on structural properties. However, lumber markets are expanding and some market segments would like to purchase lumber based on appearance in addition to structural properties. One such market segment is the wood preservation industry. Consequently, a study was commissioned to investigate the value of various attributes to buyers of softwood lumber for preservative treatment, how buyers trade-off various attributes to realize the best value, and the willingness to pay a higher price if the quality of lumber is increased beyond the minimum levels specified in the grading rules. Conjoint analysis is an appropriate tool for investigating these questions and was used in this study.

Study 2: Repaired Pallets

The pallet and container industry in the U.S. uses significant amounts of wood materials, particularly hardwood and softwood lumber. This industry is the single largest market for U.S. hardwoods. In 1993, approximately 4.82 billion board feet of solid hardwood (lumber, cants, parts, and shook) were consumed by the pallet and container industry, accounting for approximately 44 percent of U.S. hardwood lumber production (Bush et al. 1994). This industry also utilized 2.12 billion board feet of solid softwoods in 1993 (Bush et al. 1994).

However, the desire to maintain or reduce costs has resulted in increased utilization of repaired pallets. To market repaired pallets properly, it is necessary to understand user preferences. Information concerning how buyers make trade-offs among repair techniques, pallet condition, and price is particularly useful. Since the grocery industry is one of the major users of pallets in the U.S.,

buyers of recycled and repaired pallets in this market segment were contacted to investigate their preferences. Again, conjoint techniques were used to gather and analyze the data.

METHODS

The following section detail the steps taken to conduct the two studies outlined above.

Selection of Independent Variables

The preliminary variables of interest in the softwood lumber value study were drawn from Hansen's (1994) study. In Hansen's study buyers of softwood lumber for preservative treatment were asked to rate attributes based on their importance to the quality of lumber. Using these data as a starting point, the final lumber attributes and levels were developed after reviewing the literature concerning grading rules and conducting in-depth field interviews with people responsible for buying softwood lumber for preservative treatment. These attributes and their levels are shown in Table 1. Since softwood lumber prices can be quite volatile, price levels were described relative to the prevailing market price.

The attributes of repaired pallets and levels for these attributes were finalized after consulting existing literature, people in the industry, trade association personnel, and academic professionals. Table 2 provides a list of attributes and levels used in this study.

Pallet attributes were chosen to represent three general areas with which buyers are most concerned: *repair techniques, condition of the pallet,* and *cost of the pallet.* The repair technique category focuses on the methods pallet recyclers use to repair broken stringers. Recyclers repair a broken stringer by attaching a *full* or *half stringers* or by using *metal plating.* The condition of the pallet is related to the state of *top deckboards* and the *presence of protruding fasteners.* The primary determinant of the cost of a pallet is the initial purchase *price.*

Preference Models

A mixed model was specified for both studies. Spesifically, a part-worth model was specified for all non-metric variables (attributes), and a vector model was specified for the price attribute. The model specification for each attribute was verified after data collection and the mixed model was found to generate the best fit with the data. The general form of the two models is:

$$P_{jn} = \sum_{i=1}^{t} f_i\left(X_{jni}\right) + V_p X_{jnp} \qquad (5)$$

Where

- P_{jn} = perceived value or likelihood of purchase of the j^{th} (lumber pack or repaired pallet product) stimulus or profile for the n^{th} respondent
- t = total number of categorical (non-metric) attributes (five in both studies)
- X_{jn} = the level of the i^{th} attribute for the j^{th} stimulus facing n^{th} respondent
- f_i = the function denoting the part-worth of different levels of X_{jni} for the i^{th} attribute
- V_p = vector coefficient for the attribute price *(p)*
- X_{jnp} = the level of price *(p)* attribute for the j^{th} stimulus facing n^{th} respondent

Conjoint Designs

In both studies, the full-profile method was used to collect data. An orthogonal fractional factorial design (Green 1974) was utilized in both studies to reduce the judgement burden

imposed on respondents. This type of design is useful for investigating the main effects of attributes on respondent judgments. Sixteen and twenty five stimuli were generated for study 1 (lumber value) and study 2 (repaired pallets), respectively, using the "Conjoint Designer" software developed by Bretton-Clark (1990). These numbers represented the minimum possible number of stimuli, given the number of attributes and levels, and correspond to the typical practice of attempting to minimize respondent fatigue (Green 1974, Greenberg 1986).

Four additional profiles were included in each investigation to serve as holdout cards. The purpose of holdout cards is to assess the reliability of the estimated parameters. Respondents rate these holdout cards but their ratings are not used to estimate the parameters. of the models. Holdout cards facilitate testing of the stability of the model beyond the data with which the parameters were estimated and are the most commonly used method of assessing the cross-validity or reliability of estimated parameters (Bateson et al. 1987).

Stimulus Presentation

In study 1, a verbal description (profile card) approach was adapted to present each profile to respondents (buyers of softwood lumber). All twenty stimuli were presented to lumber buyers in a questionnaire. This method was utilized as some of the attributes were abstract and, therefore, could not be presented in pictorial form. Figure 1 provides an example of a profile card used in study 1.

In study 2, pictorial props were used to collect preference data from the users of repaired pallets. Pictures make the respondent’s task easier and convey information in an unambiguous manner. Figure 2 depicts one of the stimulus cards used in the study. One master pallet was altered in accordance with the specification of each pallet profile. In each prop, up to three pictures were provided. The first picture provided an overall view of the pallet, and the remaining two pictures (where needed for clarity) were taken at close range to highlight those attributes that were altered in each profile.

Dependent Variable and Measurement Scale

In study 1, the dependent variable (perceived value) was measured using a seven-point rating scale, where 1 indicated *poor value* and 7 indicated *excellent value.* A general definition of value (quality for the price) was provided in the survey instrument.

In study 2, the dependent variable was likelihood of purchasing the repaired pallet. Each respondent was presented one card at a time and asked to indicate their likelihood of purchase on a nine point rating scale, where 1 indicated *very unlikely to purchase* and 9 indicated *very likely to purchase.*

Data Collection

In study 1, data were collected through a mail questionnaire to buyers of softwood lumber for preservative treatment in the U.S. A pilot study was conducted by mailing the questionnaire to fifty subjects selected randomly from the sample frame. This was done to assess the response rate and improve the quality of questions. Based on the results of the pilot study, minor modifications were made to the survey instrument. Dillman's (1978) suggestions were followed while developing the survey

instrument, postcards, cover letters, and for mailing postcards and questionnaires. The modified questionnaire was sent to all remaining buyers in the sample frame. This resulted in 151 responses, which is art adequate number when the sample is relatively homogeneous[3]. After adjusting for bad addresses and buyers who did not treat softwood lumber, the response rate was 43.6 percent (151 out of 346).

In study 2, sixty buyers of recycled and repair pallets in the U.S. grocery industry were personally interviewed. One of the authors traveled to the participants' facilities to conduct the interview and collect rating data using the profile cards. This allowed us to probe the respondent to gain insights and information not available from a mail questionnaire.

Estimation Procedures

Both studies used the Conjoint Analyzer software distributed by Bretton-Clark (1992) for data analysis. This software uses ordinary least square (OLS) regression to estimate the model parameters. Respondent's rating scores were treated as dependent variables and attribute levels were treated as values of independent variables in the regression. The levels of the non-metric independent variables were dummy coded prior to the regression. The estimated parameters are referred to as part-worths or utility scores. They indicate the degree of importance of each attribute level to the buyer in the formation of preferences. As mentioned previously, the model parameters were estimated on an individual respondent basis and aggregated to estimate the overall model.

[3]The sample was assumed to be homogeneous since respondents are one softwood lumber customer group. Cluster analysis of the data confirmed that respondent preferences are relatively similar.

Simulation and Sensitivity Analysis

A first-choice (max-utility) rule simulator was used to perform simulations and sensitivity analyses in both studies and the sensitivity of respondents to changes in attribute levels and price was determined. While manipulating attribute levels, one attribute at a time, and price, the proportion of respondents preferring each product profile in the scenario was noted. This type of analysis helped to determine how respondents trade-off quality for price or vice versa.

INTERPRETATION

Utility or part-worth scores for each attribute are the primary results a researcher obtains in a conjoint study. How can one interpret these results? What else can a researcher do with these results? The following sections answers these questions by interpreting the results obtained in studies 1 and 2.

Utility Scores

Utility scores indicate the influence of each attribute level in the formation of respondent preferences (or any dependent variable) for the overall product. In other words, utility scores represent a respondent's degree of preference for each level of each attribute. Utility is measured in common interval-scaled units. Consequently, preferences for different attributes can be compared and added together to determine the overall preference for a product." Conjoint analysis uncovers a separate utility function for each attribute and for each respondent.

In both studies, the individual respondent's utility scores were aggregated and averaged to obtain an overall preference structure (utility function) for each attribute. All respondents' utility scores were averaged as the results of cluster analyses of utility scores indicated that respondent preference structures for each attribute were similar. Figures 3 and 4 illustrate the preference structure for each attribute in studies 1 and 2, respectively. The utility scores in these figures were adjusted so that the least preferred level of an attribute will always have a zero utility score.

Study 1

The utility scores shown in Figure 3 reveal that softwood lumber buyers prefer the following level of each of the five attributes: *no wane, $5/mbf below the current market price,* a lumber pack with *99% of its pieces on-grade or better, straight lumber,* and a lumber pack with *no forklift damage.* Although these utility functions confirmed the obvious (i.e., buyers prefer higher quality over lower quality and lower price over higher prices), they also express buyer preferences in quantifiable terms and show the strength of the preference. For example, the utility function for *wane* shows that buyers' preference for lumber increases approximately in proportion to the decrease in the amount of wane in lumber from *maximum allowable wane* to *pencil wane* and *pencil wane* to *no wane.*

Let us consider the utility functions for *wane* and *price.* First, the conjoint analysis shows that the average respondent's preference for lumber is highest if the lumber pack has *no wane* and declines with increases in the amount of wane. The analysis also shows that the respondent's preference for lumber pack is strongest at *$5/mbf below the current market price* and decreases as the price increases. Second, it shows that *wane* has a stronger influence (range of utility scores) on the respondent's overall preference for lumber than does *price.*

Third, the utility functions allow us to compute the degree of preference the buyer has for any of the attribute combinations. For example, the *no wane* and *$5/mbf above the market price* combination of profile has a combined utility score of 1.97 (1.49 + 0.48), whereas the *pencil wane* and *same as the market price/mbf* has a combined utility score of 1.63 (0.67+ 0.96).

Clearly, the respondent exhibits a stronger preference for the first wane/price combination. The overall utility of these two combinations also illustrate the kinds of trade-offs respondents make in deciding among multiattribute products. Here, even though the second profile has lower price, the average respondent is willing to trade-off some of the utility of low price for the added utility of no wane. This is evident since the combined utility of the first combination is higher than that of second combination. Respondent's trade-offs for the remaining attribute combinations can be observed using the utility scores.

Study 2

The utility scores in this study indicate the impact of each level on the likelihood of respondents purchasing the repaired pallet. The preference structure of an average repaired pallet user for each attribute is shown in Figure 4. The results indicate that pallet end-users prefer a repaired pallet that has *no half* or *full stringer* attached to its original stringer, has no *metal plate,* has no

protruding fasteners, has all *top deck-boards intact,* and costs $3.00. Again this combination represents the predictable result of preferring high quality at low price.

Preference (utility) is greatest for a pallet with *no half attached stringer.* The preference for a repaired pallet decreases as the number of *half attached stringers* increases from none to two. The steep slope of the utility function for *half attached stringer* shows that any time a half stringer is attached to a pallet, buyers' preference toward that pallet diminishes substantially. This utility function also shows that buyers are more sensitive to the introduction of the first half attached stringer than to the introduction of any additional half attached stringers. The results shown in Figure 4 can be interpreted in the similar fashion for the remaining attributes.

The utility functions for various pallet attributes indicate how users perceive trade-offs between attributes. For instance, the average user of repaired pallets will trade-off *protruding fasteners* to obtain a pallet with *no half attached stringer.* This is because the additional utility to the pallet user that is derived by moving from *one half attached stringer* to *no half attached stringer* is greater than what is lost from trading down to a *pallet with protruding fasteners* from a pallet with *no protruding fasteners.* Figure 4 also indicates that the pallet user will trade-off lower prices in favor of obtaining the most preferred levels of all other attributes except *metal plating (plated stringers).*

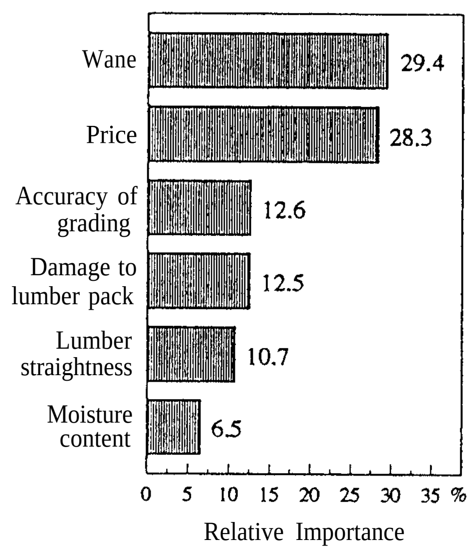
Relative Importance

The estimated utility scores also help determine the relative importance of each attribute in the preference structure. Relative importance indicates the position of each attribute, in relation to all other attributes, in influencing a respondent's decision. If the relative importance of one attribute is found to be twice that of the second, it can be inferred that the first attribute has twice the influence of the second. The relative importance score of an attribute can be calculated by dividing the utility score range[4] of that attribute by the sum of utility score ranges of all attributes. This can be indicated in percent by multiplying the resulting value by 100. Thus, the sum of relative importance of all attributes equals to 100.

Study 1

The relative importance of various attributes in the determination of lumber value are shown in Figure 5.

FIGURE 5. RELATIVE IMPORTANCE OF ATTRIBUTES IN THE DETERMINATION OF LUMBER VALUE.



The largest bars for *wane* and *price* indicate that these attributes are the most important determinants of perceived value to buyers of softwood lumber for

[4] The difference between the utility score of the most preferred level and the utility score of the least preferred level of the attribute.

preservative treatment. Buyers trade-off better levels of attributes that have smaller bars for the better levels of attributes that have larger bars in the graph. The data in Figure 3 indicate that lumber buyers prefer lumber with *19% moisture content* over lumber with *25% moisture content.* [5] However, Figure 5 indicates that this attribute is of very little importance to softwood lumber buyers when compared to other attributes. In fact, the utility functions indicate that the average buyer would trade-off *19% moisture content* for better quality levels of more preferred attributes, such as *wane, price, lumber straightness.*

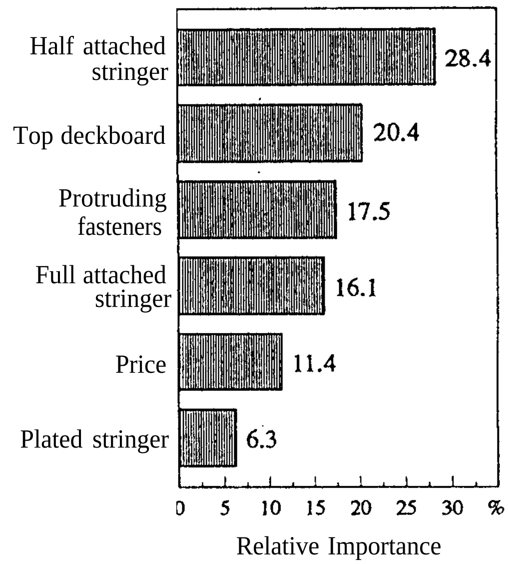
Study 2

The relative importance shown in Figure 6 indicates how much each attribute contributes, in relation to other attributes, to the formation of buyer preferences (likelihood of purchase) for a repaired pallet.

Of all attributes, *half attached stringers* have the greatest impact on buyers' preference for a repaired pallet. The relative importance of this attribute was 28.4 percent. The *top deckboard* with a relative importance of 20.3 percent represented the second most significant factor in purchase decisions. Collectively, these two attributes accounted for almost one-half of the respondents' repaired pallet preference. Figure 6 illustrates the relative importance of all of the attributes included in the study.

[5] Figure 3 also shows that the average respondent preferred *25% MC* over *22% MC.* However, there is no statistically significant difference between the utility scores of these two levels.

FIGURE 6. RELATIVE IMPORTANCE OF VARIOUS ATTRIBUTES IN THE DETERMINATION OF PREFERENCE FOR REPAIRED PALLETS.



Trade-offs Between Quality and Price

Simulation analyses were used to understand buyer trade-offs between quality and price and to learn the differential price point at which buyers prefer two products equally, even though the quality of one product is superior to the quality of the other product.

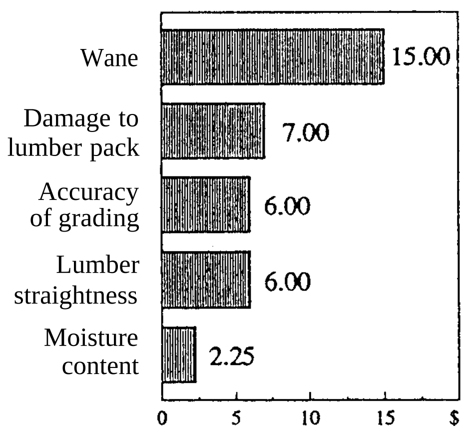
Study 1

Figure 7 illustrates the additional amount softwood buyers will pay per mbf for lumber with the most preferred level as compared to the least preferred level of each attribute. For example, buyers will pay up to $15.00/mbf more for wane free lumber than for lumber with maximum allowable wane. At the price difference of $15.00/mbf, buyers will be indifferent between the two offerings (no wane lumber pack and maximum allowable wane lumber pack), assuming similar knowledge and market access (awareness and distribution, for example). At this price difference, the percentage of respondents preferring *no*

wane lumber and *maximum wane* lumber becomes roughly equal.

Softwood lumber buyer trade-offs between other quality attributes and price can be interpreted in the similar fashion. For instance, suppliers who provide lumber with no forklift damage can command a price premium of $7.00 over competitors who provide lumber with minor forklift damage.

FIGURE 7. THE ADDITIONAL AMOUNT TREATERS ARE WILLING TO PAY PER MBF FOR THE MOST PREFERRED LEVEL AS COMPARED TO THE LEAST PREFERRED LEVEL OF EACH LUMBER ATTRIBUTE.



Study 2

The sensitivity of repaired pallet users to various attributes and price was determined in a manner parallel to that used for the softwood lumber study. Pallet users were most sensitive to *half attached stringers* and traded low price to obtain this attribute. Even at the price difference of $3.90 between the pallet with *no half attached stringers* and the pallet with *two half attached stringers,* given the quality of all other attributes is held constant, a significantly higher percentage of pallet users (74% *vs.* 26%) preferred the former pallet (no half stringers). Also at a price difference of $3.90, the percentage of respondents preferring *no half attached stringer* pallet was significantly higher (68% *vs.* 32%) than those preferring *one half attached stringer.* However for the attributes *protruding fasteners, metal plating,* and *top deckboards,* the difference between the percentage of respondents preferring a pallet with the least preferred level and the percentage of respondents preferring a pallet the most preferred level becomes insignificant at a price difference between $1.20 to $2.70.

SUMMARY AND CONCLUSIONS

Conjoint analysis can be used to understand the preference structure used by customers when selecting products. This paper provided a non-technical description of various steps involved in a conjoint study while briefly explaining the different options available in each step. The results of two studies were used to discuss the various steps and results of conjoint analysis.

A researcher preparing to use conjoint analysis in a study should plan carefully to obtain reliable data. Attribute selection is the most crucial step since researchers must make subjective judgments and the remainder of the analysis is predicated on the significance of the included attributes. The availability of several specialized conjoint software packages makes the task of undertaking the remaining steps in a conjoint study easier. These steps include selecting preference models for each attribute, determining the stimulus form to use for data collection, selecting an approach to present stimuli to subjects, deciding on a measurement scale for dependent variables, selecting a procedure to estimate utility scores, and determining the type of choice simula-

tors to be used to investigate sensitivity to various quality and price combinations.

We hope that this paper will spark the interest in this useful technique among forest products marketers. Further, we hope that this paper will serve as a resource for people beginning to investigate conjoint analysis.

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APPENDIX

TABLE 1. ATTRIBUTES AND LEVELS USED TO ESTIMATE SOFTWOOD LUMBER VALUE.

ATTRIBUTE	**LEVELS**
Accuracy of grading	**95%** of the pieces in the lumber pack are **on-grade** or better
	97% of the pieces in the lumber pack are **on-grade** or better
	99% of the pieces in the lumber pack are **on-grade** or better
Wane	Less than 50% of the pieces in the lumber pack have **maximum allowable wane**, and the rest have no wane
	Less than 50% of the pieces in a lumber pack have **pencil wane**, and the rest have no wane
	All pieces in the lumber pack have **no wane**
Moisture content	All the pieces in the lumber pack have **25%** or less **MC**
	All the pieces in the lumber pack have **22%** or less **MC**
	All the pieces in the lumber pack have **19%** or less **MC**
Lumber straightness	Less than 10% of the pieces in the lumber pack have **maximum allowable warp**
	All the pieces in the lumber pack are **straight**
Damage to lumber pack	Lumber pack has **minor forklift damage**
	Lumber pack has **no forklift damage**
Price/mbf	**$5 below** the current market price
	Same as the current market price
	$5 above the current market price
	$10 above the current market price

TABLE 2. ATTRIBUTES AND LEVELS USED TO QUANTIFY THE LIKELIHOOD OF PURCHASING REPAIRED PALLETS.

ATTRIBUTE	LEVELS
Half attached stringer	**No half stringer** is attached to any of the original stringers
	One half stringer is attached to one of the original stringers
	Two half stringers are attached to the original stringers
Full attached stringer	**No full stringer** is attached to any of the original stringers
	One full stringer is attached to one of the original stringers
Metal plating	No plated stringer
	One plated stringer
Protruding fasteners	Present
	Absent
Top deckboard	All top **deckboards are intact**
	One top deckboard is **broken**
	Two top deckboards are **broken**
Price/unit	$3
	$4
	$5
	$6

FIGURE 1. AN EXAMPLE PROFILE CARD USED TO COLLECT DATA CONCERNING THE PERCEIVED VALUE OF SOFTWOOD LUMBER.

95% of the pieces in the lumber pack are *on-grade or better.*
All the pieces in the lumber pack have *no wane.*
All the pieces in the lumber pack have *25% or less moisture content.*
All the pieces in the lumber pack are *straight.*
The lumber pack has no *forklift damage.*
Price: *same* as the current market price/cbm.

Please circle the number that best represents the value (i.e., quality for the price) of the lumber pack described. Please assume the lumber package differs only on the listed characteristics, and all the other characteristics remain the same.

Poor value						Excellent value
1	2	3	4	5	6	7

FIGURE 2. EXAMPLE PROFILE CARD USED TO COLLECT LIKELIHOOD OF PURCHASING DATA FOR REPAIRED PALLETS.

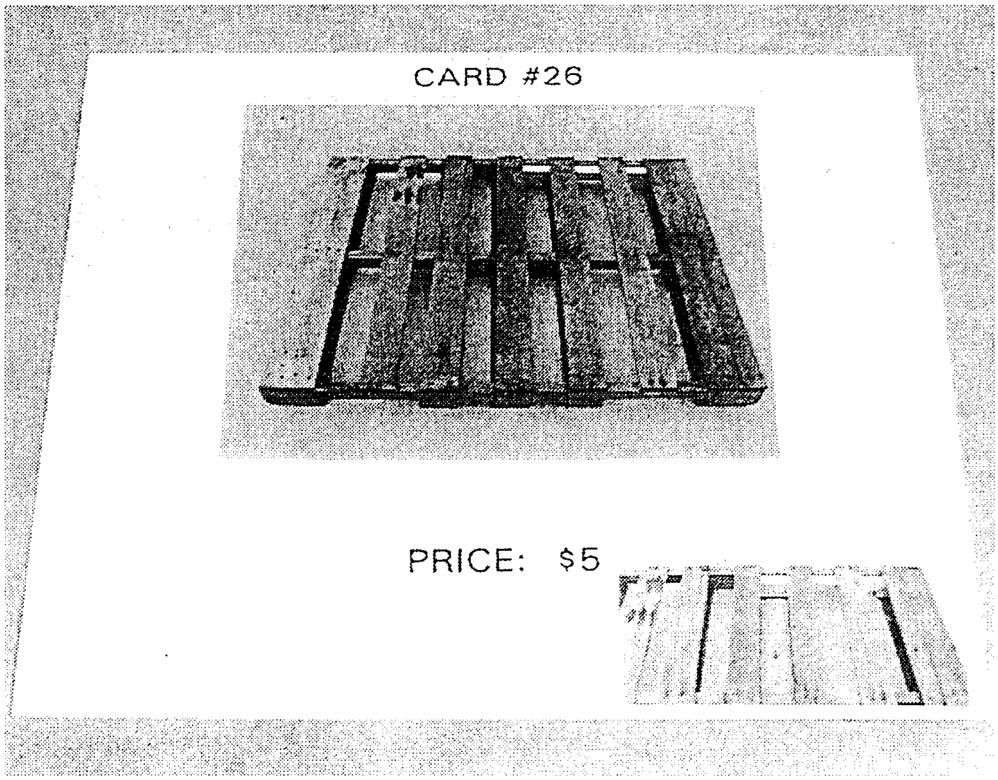


FIGURE 3. AVERAGE SOFTWOOD LUMBERR BUYER'S PREFERENCE STRUCTURE FOR EACH LUMBER ATTRIBUTE AND PRICE.

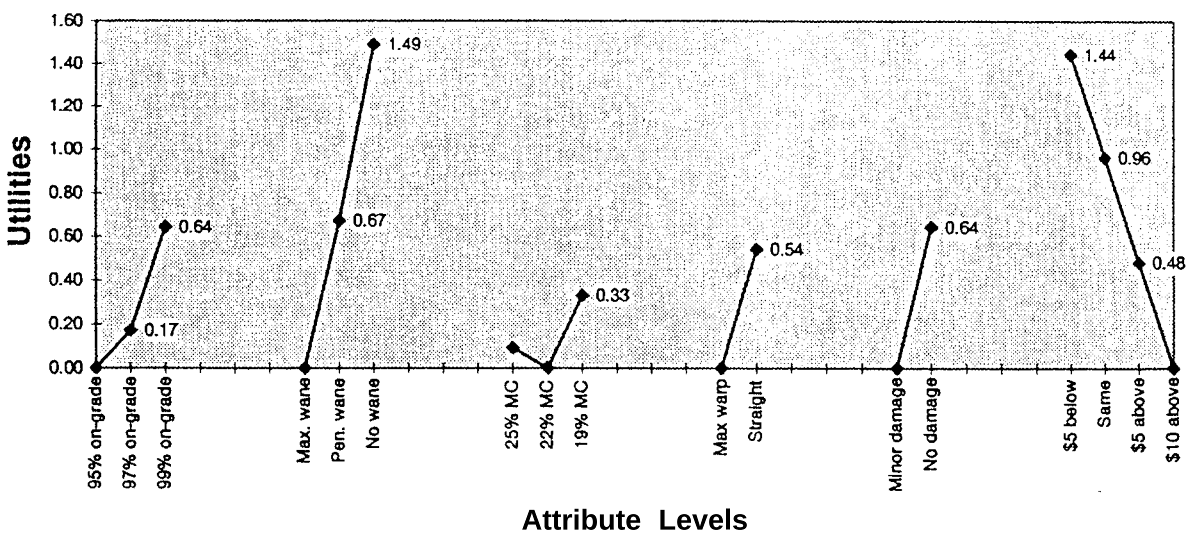
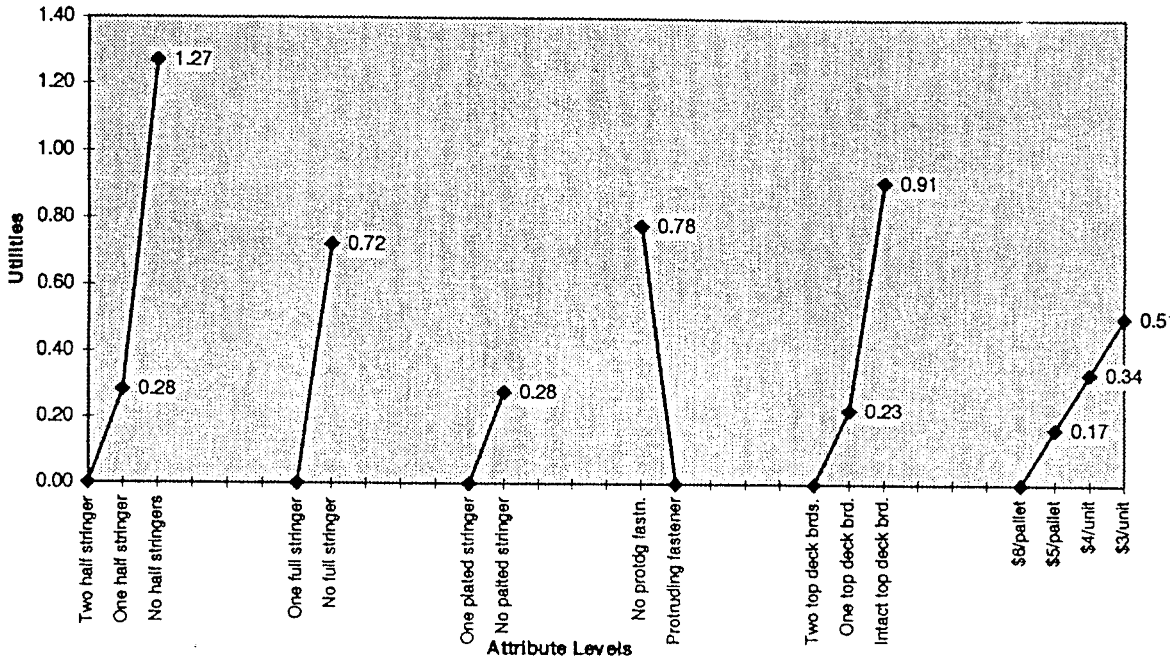


FIGURE 4. AVERAGE RESPONDENT'S PREFERENCE STRUCTURE FOR VARIOUS ATTRIBUTES OF REPAIRED PALLETS.



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