Analyzing Consumer Behavior for Setting Energy Efficiency Program Priorities

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ABSTRACT

The purpose of this paper is to provide a theoretical framework for using conjoint analysis to assist in designing energy efficiency programs. Historically conjoint has played a significant role in market research and product development. In recent years Quantum Consulting has used this tool to identify ways to look at the effects of varying rebate levels on customer decision-making criteria. In this paper, we take this application one step further by asserting that conjoint analysis can be an effective tool for developing market transformation programs. In particular, it can be useful in the design of educational or knowledge-based programs that function by promoting the benefits of energy efficient technologies to residential or small commercial customers. This paper will introduce the reader to conjoint analysis and provide illustrative examples of its application to energy efficiency program design.

Introduction

The purpose of this paper is to provide a theoretical framework for using conjoint analysis to assist in designing energy efficiency programs. Historically conjoint has played a significant role in market research and product development. In recent years Quantum Consulting has used this tool to identify ways to look at the effects of varying rebate levels on customer decision-making criteria. In this paper, we take this application one step further by asserting that conjoint analysis can be an effective tool for developing market transformation programs. In particular, it can be useful in the design of educational or knowledge-based programs that function by promoting the benefits of energy efficient technologies to residential or small commercial customers.

Conjoint analysis is a valuable tool for the design of market transformation programs primarily because it reveals detailed information about how customers make product choice decisions. It is generally accepted that the most effective marketing campaigns are those with short and simple messages. Conjoint analysis can help identify which messages will be most effective, and have the greatest impact on the targeted customers. Furthermore, potential improvements in market share resulting from educational campaigns can be assessed using conjoint analysis in conjunction with survey techniques. Comparing potential market share improvements across technologies can determine which technologies would be most cost-effective to target in educational market transformation program. When combined with demographic data or other regression analysis, the results of the conjoint can also be used to forecast market penetration of energy efficient methods under various program design scenarios.

This paper will introduce the reader to conjoint analysis by presenting the basic methodology and statistical model. The discussion will then explore some important issues to consider when applying the method. Particular attention is paid to the calculation and interpretation of *importance statistics*, which quantify the relative importance of product features. Applications to market penetration forecasting are discussed, including an example showing the accuracy of a previously built market penetration model. Finally, a specific application of conjoint analysis to the design of educational and knowledge-based market transformation programs is presented with the aid of a hypothetical example.

What is Conjoint Analysis?

Conjoint analysis is a well established market research technique that is often employed to determine preferences for different products. It can be used to quantify the degree of preference for specific attributes or features, and the relative importance of attributes themselves.

Conjoint analysis involves having respondents sort through and rank cards showing different product characteristics. Each card has a different set of product attributes, representing a different product choice. Respondents are asked to rank cards in order of their preference. Since each card contains several characteristics of the product, respondents are forced to decide which characteristics are most important. For example, consumers may prefer refrigerators that are large, frost free, and have a low price. Respondents are forced to tradeoff these attributes, revealing the relative importance of each.

Conjoint analysis has the advantage of introducing hypothetical features into the analysis. For example, characteristics that currently do not exist in the market, such as different efficiency levels, or different financing options, or other attributes being considered for a new product or program. The impact of this new feature can be evaluated through conjoint analysis.

Estimation is calculated based on the card rankings and the values of attributes on the cards. This provides an estimate of how attribute levels affect card rankings and is used to estimate total utility for each product or equipment option. Using a slightly different version of the logit model, the rankings of the cards are regressed against the attribute levels on the cards. This has a different appearance than the standard conditional logit since the dependent variable is the actual ranking rather than a zero or one value.[1] However, estimation of this model is conducted the same as with the more familiar logit specification. The equation to be estimated in this stage is given by;

$$\text{Rank}_i = \Sigma_J \beta_j' X_{ij} + \varepsilon_i$$

Where Rank_i = The ranking of card i

X_{ij} = Value for attribute j from card i

β_j = Coefficients to be estimated

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[1] A more complete description of how ranked conjoint data can be analyzed using this logit specification is contained in “Logit Models for Sets of Ranked Items”, Nicholos Christakis and Paul Allison, *Sociological Methodology*, Volume 24, 1994, pp. 199-228.

ε_i = Random error term assumed to be logistically distributed

Exhibit 1 shows individual level data that would be used to estimate the equipment choice model using the example of clothes washer equipment. In this example, there are six attributes, and each attribute has two or three levels. Each row represents a different card, and the rank of the cards is regressed against the attributes, as described above.

Using these estimated results, a clothes washer choice set is constructed that reflects both standard and high efficiency equipment options. Using the logit density function, the probability of choosing any option n among M different equipment options given that a purchase is made is

$$\text{Prob}(\text{Equip}_n \mid \text{Purchase}) = \exp(\beta' X_n) / \Sigma_M (\exp(\beta' X_m))$$

Dependent Variable	**Independent Variables**					
Rank	**Price**	**Savings**	**Door Placement**	**Capacity**	**Water Temperature**	**Load Size Adjustment**
1	400	50	Front	Standard	Warm, Cold	Non-Adjustable
2	400	50	Top	Standard	Hot, Warm, Cold	Adjustable
3	400	10	Front	Standard	Hot, Warm, Cold	Non-Adjustable
4	400	10	Top	Standard	Warm, Cold	Adjustable
5	400	0	Front	Extra Large	Hot, Warm, Cold	Non-Adjustable
6	400	0	Top	Extra Large	Warm, Cold	Adjustable
7	400	0	Front	Extra Large	Warm, Cold	Non-Adjustable
8	400	0	Top	Extra Large	Hot, Warm, Cold	Adjustable
9	450	50	Top	Extra Large	Warm, Cold	Non-Adjustable
10	450	10	Top	Extra Large	Hot, Warm, Cold	Non-Adjustable
11	450	0	Front	Standard	Warm, Cold	Adjustable
12	450	0	Front	Standard	Hot, Warm, Cold	Adjustable
13	650	50	Front	Extra Large	Hot, Warm, Cold	Adjustable
14	650	10	Front	Extra Large	Warm, Cold	Adjustable
15	650	0	Top	Standard	Warm, Cold	Non-Adjustable
16	650	0	Top	Standard	Hot, Warm, Cold	Non-Adjustable

Exhibit 1- Hypothetical Example - Individual Ranked Conjoint Data For Equipment Choice Estimation

Past experience as well as existing literature indicates that the most successful conjoint designs limit each exercise to ranking 16 cards at a time with 4 to 6 attributes on each card. Including more cards or additional attributes tends to overwhelm respondents and results in less reliable data.

In addition, attributes must be perfectly uncorrelated across the deck of card choices. This is known as orthogonal design, and has several advantages. By randomly assigning attribute levels, respondents are forced to make tough tradeoffs by deciding which attributes are most important. For example in the real marketplace, high electricity savings may come at the expense of higher equipment costs. If this were reflected in the cards with savings and price correlated, the difference in ranking due to either equipment, price or savings cannot be determined from the data. Having the attribute levels randomly assigned in an orthogonal design mitigates this program.

When is Conjoint an Appropriate Tool?

Conjoint works the best to analyze the decision process for products that are fairly homogeneous, with a manageable number of defining features. This can usually be achieved by creating a sufficiently narrow product definition. For example, residential Central Air Conditioners would be a good candidate for conjoint analysis. There are relatively few differentiating features, such as efficiency, cost, and durability. On the other hand, the broader category of HVAC would not be easily analyzed with conjoint because the defining characteristics would have to incorporate too many features to be reasonably comparable.

Similarly, fluorescent tube lights are an example of a product that could be analyzed well with conjoint analysis. The differences between fluorescent tubes can be reasonably reduced to a manageable number of features. For example initial cost, energy efficiency, light color, and flicker. On the other hand, commercial lighting is too general a category, with too many defining features to reasonably be captured in 4 to 6 attributes on cards.

Important Considerations

For conjoint results to be accurate, the card features must be independent. That is, we must make the assumption that product attributes are evaluated independently of each other, and do not have distinctly different effects when combined in certain ways. If the ultimate intention of the model is to predict product purchases or market penetration of equipment options, the card features must also reasonably define the product. A clear example of this is price. Price is almost always a consideration in product choice. Leaving price out would greatly reduce the model's ability to predict purchases. Finally, conjoint analysis cannot capture the effects of brand loyalty when presenting cards with generic attributes. As with all stated preference techniques, the researcher is relying on the respondent's ability to accurately describe their actions in a hypothetical situation. This is always a consideration, but can be more of a problem when respondents are asked to assess the attractiveness of products that are either not physically or logically compatible, such as an over-sized refrigerator with the lowest energy use and lowest price.

Another important issue to consider is the artificial elevation of the importance of attributes. Because a product is reduced to 4 to 6 attributes, there is a built in bias to exaggerate the importance of each. For example, for the consumer who normally pays little attention to energy savings, may be more likely to pay attention to this factor as it is one of the features on the cards.

It is also important to choose attributes that are easily and uniformly definable. If attributes with subjective aspects must be chosen for the conjoint, visual or physical demonstration should be used to ensure that respondents are evaluating the same attribute. For example a "noisy" refrigerator may have different interpretations by different respondents. Without audible demonstration of “noisy” and “quiet” the conjoint results would be impossible to interpret.

Care must be taken when designing conjoint cards to create appropriate levels for each attribute. Conjoint results do not extrapolate consumer sensitivity beyond the ranges present in the cards, thus the range of interest for each attribute must be included. In addition, it is very important that the variance for each attribute on the cards must be selected to mirror reasonable and compatible choice differences. This concept is best illustrated by example: Suppose a conjoint experiment focused on refrigerators might have include size, efficiency, and durability and price as card attributes. If size ranged from 10 cubic feet to 26 cubic feet, but price only varied between $600 and $700, it is easy to intuitively see that respondents would respond more to the size attribute than price.

Finally, conjoint analysis reveals consumers’ preferences based on their current information and beliefs about the world. The consumer may have tastes based on prejudiced beliefs that would change with hands-on experience. For example, a consumer may believe a front loading washing machines would be awkward to load. With hands-on experience, this consumer may find that front loading machines are in fact not awkward at all. Conjoint analysis cannot measure the degree of prejudice in consumers’ revealed preferences. However, serial conjoint analyses may capture changes in consumers’ preferences over time, potentially revealing impacts of market transformation programs.

Common Data Collection and Analysis Methods

Focus groups and surveys are valuable tools to enhance the value of the conjoint experiment. Focus groups can be used to identify and explore the attributes and features that are top priorities to customers in making product choices. Quantum Consulting has used focus groups for this purpose in the past. The moderator guided the discussion to get an unprompted list of the important attributes of the equipment being studied. Once the unaided list of attributes was obtained, the moderator suggested other attributes that were not volunteered initially for the group to discuss. Focus group participants were then asked to list their top ten most important attributes if they were to purchase this equipment today. The objectives of the study, together with the results of focus group research are extremely useful in determining the 4 to 6 attributes to include on the cards.

Surveys are also key components of a well designed conjoint experiment. Certain attributes such as age, income, housing type and climate zone should be collected up front and used to construct a balanced sample for the conjoint and focus group participation. More detailed surveys, administered during the conjoint sessions for example, can be used to collect more detailed data from conjoint participants. For example, information about energy efficiency equipment and program awareness, attitudinal data, past equipment experience, equipment purchases, and more can be used to stratify the sample.

Using demographic data to stratify the sample can provide the researcher with information about differences between the decision processes and priorities across different population segments. This can provide for effective tailoring of energy efficiency programs to different target population segments.

Importance Statistics

The value placed on different attributes during the conjoint analysis can be used to calculate *importance statistics* for each equipment attribute. The importance statistics illustrate the contribution that each attribute makes towards the total utility associated with the equipment as defined by the attributes. The larger the importance statistic, the greater the value placed on that attribute.

For example, during 1999, Quantum Consulting conducted focus groups and conjoint experiments to determine the relative importance of clothes washer features. Specifically, which clothes washer attributes consumers value most, and how changes resulting from an efficiency standard may affect consumer utility and clothes washer purchases.

Based on focus group results, the following six clothes washer attributes were selected for the conjoint: clothes washer price, energy and water savings, capacity, water temperature, door placement, and load size adjustment. Four-hundred individuals were recruited in 4 cities to rank the clothes washer cards in a moderated, central location exercise. Using the methods described in the previous section, an estimation was done based on the card rankings and the values of attributes on the cards. The results of this equipment choice model were used to infer the relative importance of each attribute to the consumers' total utility. Specifically, the coefficient estimates from the equipment choice model were used to calculate the "importance statistic." This statistic measures the importance of one design attribute, relative to that of all other design attributes in determining a card's total utility.

The total utility of each card can be calculated by inserting attribute values into the estimated regression equation:

$$\text{Total Utility}_i =$$
$$\beta_1\text{'Price}_i + \beta_2\text{Savings}_i + \beta_2\text{DoorPlacement}_i + \beta_3\text{Capacity}_i + \beta_4\text{WashTemp}_i + \beta_5\text{LoadSize}_i$$

Using the coefficient estimates and the values for the attributes used in the conjoint analysis, the importance statistic is defined as:

$$IMP_I = \frac{\Delta Yi}{\Delta y} = \frac{\text{The\_maximum\_utility\_change\_due\_to\_attribute\_i}}{\text{The\_maximum\_utility\_change\_due\_to\_all\_attributes}}$$

The importance statistic measures the percentage of the total maximum change in utility across all card choices that are attributable to a single attribute. Stated another way, the importance statistic measures each attribute's contribution to the total utility based on the six attributes included in the conjoint analysis. Some literature indicates that there may be an upward bias in the importance statistics of attributes that vary more across the cards. That is, attributes that have more levels or more disparate levels across the cards may have a slightly exaggerated importance statistic. This is a result of respondent's psychological response to additional levels, as well as the conjoint experiment design. As discussed previously, the range of variance for each attribute on the cards must be selected to mirror reasonable and compatible choice ranges.

The estimated coefficients for each clothes washer attribute, as well as each relative importance statistic are presented in Exhibit 2.

	Coefficient	Standard Error	Significance Level	Relative Importance
Price	-0.00359	0.000	1%	26%
Savings	0.010	0.001	1%	14%
Capacity	0.248	0.024	1%	7%
Door Placement	0.383	0.024	1%	11%
Wash Temp.	0.614	0.024	1%	18%
Adjustable	0.852	0.024	1%	25%
				100%

Exhibit 2 - Regression Coefficients and Relative Importance - All Respondents

The coefficient estimate for price is negative and significant and the estimate for savings is positive and significant. All of the remaining attributes are statistically significant, with positive coefficient estimates. A positive coefficient for "Capacity" indicates people prefer extra-capacity machines to standard capacity. Regarding door placement, respondents indicated a preference for top-loaders over front-loaders. Having a hot water wash option was attractive, as was the ability to adjust the water level to match the size of the load. All of these coefficients are significant at the 1 percent level of significance, which means that the estimates are significantly different from zero with a 99 percent degree of confidence.

While coefficient estimates do provide some information on the influence of the variable on total utility, it is misleading to look only at the coefficient to gauge the influence of that variable. For example, the savings coefficient is ten times the magnitude of the price coefficient since savings is measured in tens of dollars and price in hundreds of dollars. Only looking at the magnitude of the coefficients would give the misleading impression that savings are considered much more important than price. To address this issue, relative importance statistics are calculated that combine both the coefficient and attribute value to get an overall measure of the influence on total utility.

The relative importance statistics show that while price is the most important attribute to consumers, it just barely surpasses adjustable load size in terms of importance in total utility based on the six washer attributes. Together, these two attributes contribute about half of the total utility. The results show that people care more about having adjustable load sizes and hot water options than they do about energy savings or door placement. This indicates that it would be difficult to successfully promote horizontal axis machines, which do not include the proper equipment options. Given the high relative importance of price, rebate may also be an effective tool to promote adoption of horizontal axis clothes washers.

From Conjoint Analysis to Market Penetration Forecasts

This discussion focuses on several different approaches to using conjoint analysis for market penetration forecasting. When making market penetration forecasts we move from predicting relative to absolute consumer behavior. We must understand not only how the equipment choice decision is made, but also how the decision to purchase is made. Conjoint analysis is very good at analyzing how the equipment choice decision is made, but it is a more challenging problem to extrapolate to estimates of aggregate demand for different technologies. This section discusses two approaches. The first combines the information about equipment choice from conjoint with demographic data that predicts aggregate purchase volume. The second employs a conjoint style experiment to ascertain the attribute points where consumers are attracted into early adoption, or repelled from the market altogether.

For some equipment types, demographic data is a very good predictor of aggregate purchase volume. For example, this is true of HVAC systems, which tend to be purchased almost entirely on system failure or for new construction. Quantum Consulting has constructed such a market penetration forecasting model for residential central air conditioning units and has been running the model over the past five years. The model combines demographic data analysis and conjoint analysis results to predict the market penetration of different efficiency level equipment options. In this Market Penetration model, housing starts, demolitions, age distribution of the current stock of HVAC systems and equipment type distributions were used to predict annual HVAC purchases by segment. These results were interacted with the results of conjoint experiments that predict equipment choice based on features that reflect some program design variables, such as rebate and financing options.

Together, the demographic data and conjoint results culminate in market penetration forecasts. In the example shown in Exhibit 3, the model results were calibrated to actual market in 1996, and then used to predict market penetration rates under program design scenarios reflecting 1993 and 1998 program design standards. Exhibit 3 illustrates the accuracy of this method by comparing the predicted adoption distributions to the actual distributions for the 1993 and 1998 program years.

The exhibit shows the model to substantially over-predict the adoption higher SEER[2] units for 1993, while the predictions are somewhat better for 1998. Some of the difference in the 1993 figures can be attributed to supply side factors. The availability of equipment with a 13 or higher SEER was restricted during 1993. In order to improve the model's accuracy in this regard, supply side factors would have to be incorporated into the modeling approach.

[2] Seasonal Energy Efficiency Ratio

	1993 Program		1996 Program		1998 Program	
SEER Rating	Model Prediction	Actual Distribution	Model Prediction	Actual Distribution	Model Prediction	Actual Distribution
11	26%	48%	13%	13%	16%	9%
12	56%	48%	53%	51%	58%	55%
13	12%	3%	13%	13%	12%	16%
14	4%	1%	17%	16%	13%	17%
15	2%	1%	4%	3%	2%	3%

Exhibit 3 - HVAC Market Penetration Model Accuracy

For other equipment types, the volume of purchases are not primarily a function of equipment failures. For these equipment types, multitudes of factors impact the probability of purchase. However, if one is introducing a new equipment option of a certain type of technology to the market, it can be assumed that the aggregate purchase volume for that technology will not go down as a result of the additional choice. In this case, conjoint estimates of market share may suffice as a reasonable estimate of market penetration. Of course, it would be necessary for aggregate purchase volumes to be stable over time.

If aggregate purchase volume is not stable and is expected to be significantly affected by attributes included in the conjoint cards, the problem becomes more complex. The conjoint experiment may be expanded to estimate an upper and lower bound of the sensitivity of aggregate demand to the variation of product attributes. The problem requires a slightly altered experiment from the equipment choice model described above. In addition to having respondents rank their cards from most preferred to least preferred, a second exercise would be conducted. Respondents would be asked which equipment options they would actually purchase under alternative scenarios. For *each* equipment option, the respondent would be asked two basic questions:

> “Would you purchase this equipment if the alternative was having no such equipment?”

> “Would you purchase this equipment to replace your existing equipment, assuming it is functioning properly?”

The critical issue in this approach is that respondents not compare *across* equipment options, but rather gauge how equipment features affect their likelihood of making a purchase at all. In this example, a logit model specification in which the probability of purchase is a function of the features on the conjoint cards is estimated twice. Once reflecting the responses to the first question where the alternative to purchase was having no equipment. The results of this estimation would provide a lower bound of the sensitivity of purchases to changes in features. The second logit estimation, would reflect the responses to the second question, where the alternative to purchase was using functioning, existing equipment. The results of this regression would yield an upper bound of the sensitivity of purchases to changes in features.

Application to Market Transformation Program Design

Conjoint analysis can be used to determine which features of an energy efficient equipment option make it more attractive or less attractive relative to its non-energy efficient alternative. The essential element to this application is to select features for conjoint analysis that are high priorities to consumers, *and* distinguish energy efficient equipment from non-energy efficient equipment. When this is accomplished, the results of the conjoint analysis identify key barriers to high efficiency equipment adoption.

Lets consider an example of a typical residential indoor lighting choice, specifically the choice between incandescent and compact fluorescent bulbs. This is a good example, because residential light bulbs are a fairly homogenous good that can be defined with relatively few attributes. Attributes for the conjoint analysis might include life of the bulb, price, annual operating cost, color rendering, and start speed. The cards would mix various levels of each of these features to determine how important each feature is, independently of the others. The cards might look like this:

Card	Life	Price	Annual Operating Cost	Color Rendering/Light Temp	Start Speed (Instant=1)
1	9,000 hrs	$20.00	$15.00	Like Incandescent	1
2	1,000 hrs	$1.00	$4.20	Low Contrast/Cold Blue	0
3	1,000 hrs	$20.00	$4.20	Low Contrast/Cold Blue	0
4	1,000 hrs	$20.00	$15.00	Low Contrast/Cold Blue	0
5	9,000 hrs	$1.00	$15.00	Like Incandescent	1
6	9,000 hrs	$20.00	$4.20	Like Incandescent	1
7	9,000 hrs	$20.00	$4.20	Like Incandescent	0

Exhibit 4 - Example Cards for Residential Lighting Conjoint Study

Of course, there would be approximately 16 cards, not only 7 as shown above. For illustration purposes, let's suppose that the results of the conjoint analysis look like this:

	Coefficient	Standard Error	Pr>Chi-Square	Relative Importance
Price	-0.0389	0.0012	0.0001	29%
Oper. Cost	-0.0350	0.0058	0.0001	25%
Bulb Life	0.00005	0.000002	0.0001	24%
Light Color	0.29	0.0242	0.0001	16%
Start Speed	-0.12	0.0244	0.0001	7%

Exhibit 5 - Residential Lighting Conjoint Hypothetical Results

These results indicate that price is the most important characteristic, followed closely by operating cost, and life of the bulb. In this example, start speed is a not very significant factor in consumers' bulb choice decision. The importance statistics show that price is a significant barrier to adoption, and that operating cost and bulb life are key benefits to emphasize when promoting the technology. However, these results reveal much more than this, as will be discussed below.

If we simplify the residential light bulb choice into two basic types, incandescent and compact fluorescent, we can assess the probability of choosing each and the relative importance of each attribute in that decision. Exhibit 6 below shows how the actual characteristics of compact fluorescent and incandescent bulbs would translate into equipment choice probabilities, given the above coefficient estimates.

	Incandescent	Compact Fluorescent
Price	$1.00	$20.00
Operating Cost	$15.00	$4.20
Bulb Life	1,000 hrs	9,000 hrs
Light Color	Incandescent	Incandescent
Start Speed	0	1
Probability of Purchase	51%	49%

Exhibit 6 - Estimated Probability of Purchase in a Two Choice World - Actual Characteristics of Incandescent and CFL Bulbs - Hypothetical Results

Given the above characteristics of incandescent and compact fluorescent bulbs, these results show that the probability of choosing compact fluorescent bulbs is nearly equivalent to the probability of choosing incandescent bulbs. This indicates that the current market penetration of compact fluorescent bulbs should be quite high. Suppose also that current sales do not reflect this high level of market penetration.

In the case of many technologies, consumers may have 'outmoded perceptions,' where product attributes have improved or changed in recent times and consumers' knowledge has not been similarly updated. In other cases, consumers may just have inaccurate perceptions; for example they may have the impression that compact fluorescent bulbs last twice as long as incandescents, rather than the accurate figure of 9 times as long. In addition, it is possible that consumers have access to this information, but the information source lacks credibility. This may be the case for information coming from HVAC contractors, lighting manufacturers, and others who financially benefit from the sale of energy efficient equipment.

Conjoint results can reveal the impact of outmoded or inaccurate beliefs. Suppose survey results indicate that consumers' knowledge of compact fluorescent bulbs reflect some outmoded and inaccurate information. Survey information is used to determine what the outmoded perceptions are; the coefficient estimates resulting from the conjoint experiment show the impact of changes in the levels of each attribute within the range covered by the experiment[3].

Specifically, suppose consumers perceive compact fluorescent to have half the operating cost of incandescent, and twice the bulb life. In addition, suppose customers also are shown to believe the light from compact fluorescent bulbs is a low contrast, cold blue. Given these misperceptions, the resulting probability of choosing compact fluorescents versus incandescent bulbs would be as shown in Exhibit 7 below.

	Incandescent	Perceived CFL
Price	$1.00	$20.00
Operating Cost	$15.00	$7.50
Bulb Life	1,000 hrs	2,000 hrs
Light Color	Incandescent	Low Contrast/Cold Blue
Start Speed	0	1
Probability of Purchase	70%	30%

Exhibit 7 - Estimated Probability of Purchase in a Two Choice World - Perceived Characteristics of Incandescent and CFL Bulbs - Hypothetical Results

The results based on common misperceptions about compact fluorescent technologies reflect an equipment choice probability that perhaps is closer to the true distribution. If this were the case, our results would show that there is significant potential improvement in market share resulting from an educational market transformation program that simply distributes accurate information about compact fluorescent technology. That is, in light of these hypothetical findings, we could conclude that an information and awareness promoting campaign would be very effective for this technology. Dispelling this myth and educating the public about the characteristics of the bulbs would significantly improve the market penetration of compact fluorescent technology. Of course, to effectively dispel myths, the information must be presented by a credible source, such as Energy Star or local utilities.

It is possible that this market potential could exist and not be exploited by manufacturers for a number of reasons. For example, the manufacturers of CFLs may also produce incandescent bulbs, and would therefore not be motivated to move consumers away from incandescents. Alternatively, information from manufacturers may lack credibility.

On the other hand, if our hypothetical results had indicated that ‘start speed’ was a significant barrier to adoption, such that the model’s predicted adoption rates were close to the actual adoption rates, the conclusions would very different. We would conclude that compact fluorescent bulbs were not a good product to emphasize in educational market transformation campaigns, because the public fully understands the features of this technology, and prefers incandescent bulbs. In this case, the only way to improve the market share of compact fluorescent bulbs would be to subsidize the cost or attempt to change

[3] In so far as the set of alternative values may effect the utility of a single choice, then experiments with subsets of values may be a useful way to refine this experiment.

customers' preferences, which is perhaps an unrealistic goal. In addition, the information from this study could be passed along to manufacturers to encourage the development of a compact fluorescent with an instantaneous start.

Conclusions

The intent of this paper was to introduce conjoint analysis as a valuable tool for analyzing consumer behavior in the context of energy efficiency program design. An accurate understanding of consumer behavior is inherently valuable information for those who are designing effective programs to change that behavior. Most fundamentally, conjoint analysis can identify key barriers to energy efficient equipment adoption, and quantify the relative importance of those barriers. It can identify which technologies are more cost effective to target with educational market transformation campaigns, and which messages will be most effective.

The conjoint experiment has many benefits and applications for promoting energy efficiency. The conjoint experiment can be expanded or combined with demographic data analysis to build market penetration models, which quantify the relative benefits of different program design standards. Conjoint analysis has the advantage of being able to analyze hypothetical product or program attributes. In addition, it can identify product development goals that would boost efficient technology adoption. It is a tool that has long been used by marketing professionals to increase the demand for specific goods and improve marketing campaigns. Those in the energy efficiency profession can benefit in a multitude of ways from using these same methods.

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