Why the Light Bulb is No Longer a Textbook Example for Price Elasticity: Results from Choice Experiments and Demand Modeling Research

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ABSTRACT

An internet search for textbook examples of "price elasticity" invariably delivers the following demand equation: "the quantity of light bulbs demanded is an inverse function of the price of light bulbs" (i.e., as the price of light bulbs rises, the quantity of light bulbs demanded falls). However, is it really that simple? Recent research from California suggests that the demand for light bulbs has become increasingly more complex, as new lighting technologies serving multiple applications with varying efficiency levels have become more readily available due to changes in policies, standards, supply side business models, and ultimately consumer demand. In late 2012 and ongoing in 2013, intercept surveys with random shoppers in retail stores throughout California have been conducted to address lighting purchase decisions. Data from these surveys formed the inputs to a series of choice experiments and demand models. Preliminary results suggest that while changes in light bulb purchases remain largely influenced by price, there are a number of other factors that explain consumer choice – such as, the education and income level of the purchaser, the intended application the light bulbs and how often the light bulbs will used. Understanding and quantifying the influence of these other factors can help inform lighting policy and program design to more effectively address non-price barriers.

Introduction

Light bulbs are no longer the commodity product that they once were. Residential lighting is both a large category of electrical demand (10-15 percent of residential demand in the United States[1]) and a market that is undergoing a rapid transformation. Within the past decade, incandescent bulbs have lost their status as the near universal choice for lighting technology. In California, compact fluorescent lamp (CFL) are the preferred technology for many applications and light emitting diode (LED) lamps are now in 1 percent of sockets in California homes.[2] This market transformation is part due to energy efficiency programs that promote the adoption of relatively efficient CFL and LED bulbs.[3] The success that energy programs have had in transforming the lighting market has generated a new set of issues for efficiency program planners and evaluators. Estimating consumer response to policies and programs using basic price elasticities does not recognize the rich set of choices consumers face.

The California Public Utility Commission (CPUC) engaged DNV KEMA Energy and Sustainability (DNV KEMA) to quantify the impacts that efficiency programs have in the California residential lighting market. Two of DNV KEMA's activities for the CPUC include: (1) recording available lamp products by retail channel and (2) estimating the change in market shares of lamp technology due to the program influence. DNV KEMA is in the process of collecting data from 400

[1] DNV KEMA recently tabulated the Department of Energy's Residential Electricity Consumption Survey to see how end uses vary throughout the country; results for lighting varied between 10 and 14 percent of total household electric consumption.
[2] DNV KEMA conducted a preliminary tabulation of the 2012 California Lighting and Appliance Saturation Survey. The data from this survey have not yet been released.
[3] U.S. energy policy does not ban the sale of incandescent bulbs, as is the case in Europe and elsewhere. However, California does have policies in place that began to place limits on incandescent bulb beginning January 2011. The California policies do not affect product already on store shelves.

retail stores throughout California. Early this year, we completed the first wave of 200 stores. The second wave is underway with results due in August, 2013. At each location, DNV KEMA conducts a shelf inventory and a series of consumer intercept surveys. The shelf inventories record an inventory of available lighting products. The intercept surveys record consumer preferences for lamp technologies and attributes about purchase decisions. DNV KEMA designed the intercept survey instrument to produce data for discrete choice model of consumer choice. The discrete choice model estimates market shares for each technology by lamp style. Discrete choice models frame the probability of a consumer choosing a lamp as a response to the factors that influence the consumer's decision process. This paper primarily reports on the intercept survey and the Lamp Choice Model.

The organization of this paper is as follows. The paper first discusses the design and approach to recording consumer preferences. The approach allows us to capture preference ordering that is unique to each retail channel and tied to the consumer purchase. Next, the paper describes the Lamp Choice Model. The model is a discrete choice model that treats the choice of lamp technology as a response to characteristics of the lamp, the purchaser and the intended lighting application. The final section describes the model formulation and presents preliminary findings.

Intercept Survey Design

DNV KEMA interviewers talked to both purchasers (i.e., consumers who have lamps in their basket) and non-purchasers. The interviewers ask respondents a series of questions that explore the buying situation and another series of questions that asks the respondent to rank lamps in order of preference. The first series includes questions to understand the application use, the market segment and housing and household characteristics. What makes this survey innovative is its use of an iPad to customize a preference ranking game to the respondent's basket. The next five sections describe the categories of variables collected for the Lamp Choice Model.

Application Use

The intended application or use of a lamp is a potential explanatory variable of lamp choice. Consumers may accept a CFL twister, for example, in a closet but strongly prefer a traditional-shaped incandescent for use in a desk lamp. To address how these factors may influence consumer choice, the intercept survey asked purchasers questions about where they plan to install the lamps they were purchasing that day. These questions were only asked of purchasers who indicated that they planned to install a lamp within the next week. This was done to improve the reliability of the responses. The interviewers collected following variables:

- Room type—e.g., living room, kitchen
- Fixture type—e.g., ceiling, table lamp
- Dimmable required—whether the lamp will be in a fixture with controls for dimming
- Three-way required—whether the lamp will be in a fixture with three-way controls

Market Segmentation

The intercept survey also asks a series of questions to understand whether the respondent is making a targeted or opportunistic purchase. Consumers that target their shopping to a particular store to buy a particular lamp will react differently to prices than an opportunistic shopper. The targeted shopper will be relatively price inelastic compared to the consumer who decides to buy a lamp more impulsively (e.g., after seeing promotional displays or discounts in the store). The Lamp Choice Model can be designed to have different price elasticities through market segmentation. The intercept survey contains the following variables that describe the market segmentation of the consumer:

- Targeted store—whether the respondent intend to buy lamps at this store
- Targeted style—whether the respondent intended to buy the lamp style

- Targeted technology—whether the respondent intended to buy the lamp technology

Housing and Household Characteristics

The choices consumers make vary with the structure and size of the consumer's housing and household structure. Highly educated consumers may be, for example, more likely to buy LED or CFL lamps. The intercept survey contains the following variables related to housing size and household structure:

- Bedrooms—number of bedrooms in the house
- Bathrooms—number of bathrooms in the house
- Occupants—number of people who live in the household year round
- Education—highest level of education completed
- Household income—household income in categories

Preference Ranking and Quantity Response

The last component of the intercept survey consists of two parts:

- **Preference ranking**—the survey instrument presents a set of lamps (see example for A-lamps and Twisters in Figure 1). The set of lamps in a preference ranking or ordering is known as the choice set. Each lamp in the choice set is a close substitute for the other lamps. The survey instrument constructs choice sets dynamically. If the respondent's lighting application requires a dimmable or three-way lamp, all the lamps in the choice will have that feature. The only differences between the lamps are the prices and technologies.

  The choice sets only include lamps that a consumer is likely to find in the retail channel where the survey takes place. For example, a respondent will not see a LED lamp as part of the choice set in the discount channels as discount channel stores typically do not stock LED lamps. Additionally, the survey instrument tailors the choice set to the contents of a respondent's basket. Respondents that intend to purchase a lamp see the lamp in their basket as one of the choices.

  This approach guards against data quality issues that arise when working purely with hypothetical (i.e. stated preference) data. Also, the survey instrument randomizes the prices. The price variation is consistent with typical prices by retail channel. Varying the prices exposes the estimator to the trade-offs between prices and features that consumers make.
- **Price quantity response**—the survey instrument takes the preferred choice from the ranking exercise and asks the respondent how many lamps he or she would buy. The instrument then varies the price up and down and asks again for the quantity that the respondent would buy. As above, the price variation is consistent with prices typically found in the retail channel. The result is the quantity a consumer would buy at three price points. This information is useful for calculating the demand response to price.

Figure 1. Sample Lamp Preference Ranking in the Survey Instrument

Data Description

The Lamp Choice Model uses preliminary data from the 2012 intercept surveys. The data contain 1,070 intercept interviews: 598 non-purchasers and 472 purchasers. Figure 2 shows the number of respondents by retail channel and survey type. The home improvement, mass merchandise and membership club retail channels had substantially more purchaser than non-purchaser surveys. In the grocery, drug and discount channels, interviewers were not as successful in finding purchasers. Hardware stores have a near even split between purchasers and non-purchasers.

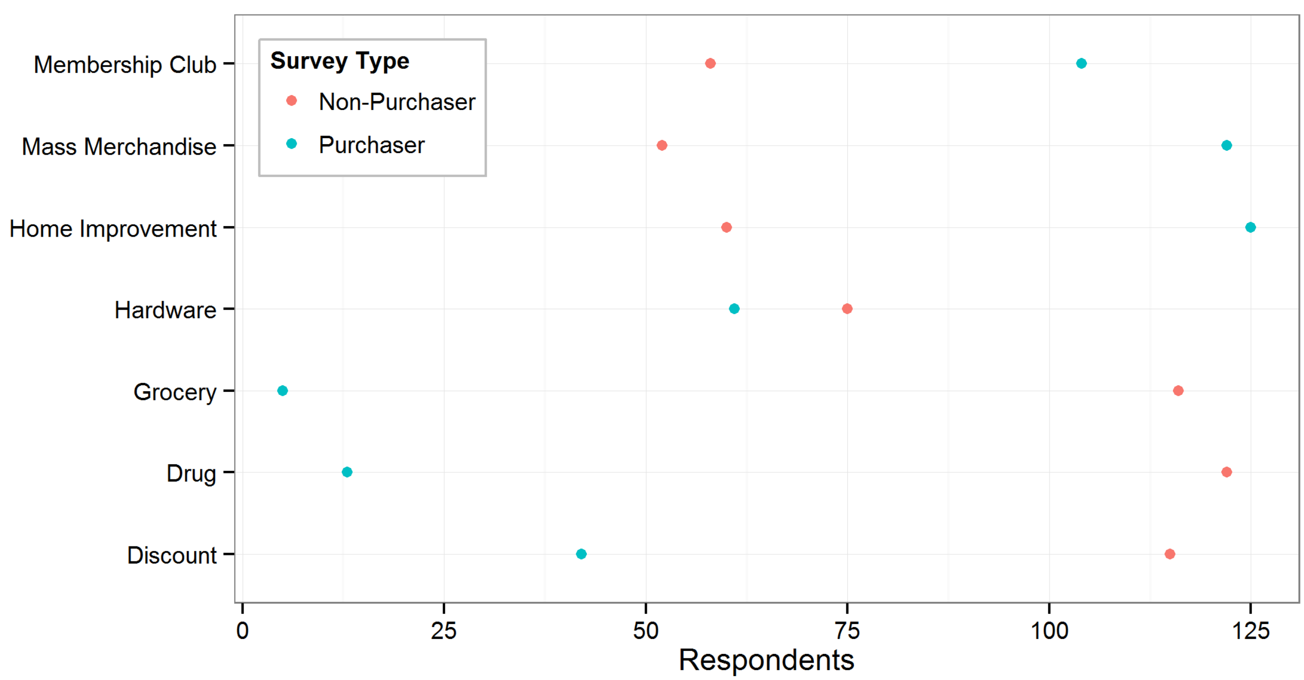

Figure 2. Respondents by Retail Channel and Survey Type

Figure 3 shows the number of observations by the preferred lamp technology for each lamp style. Successful logit model estimation generally requires over 200 observations. Further, respondents must not all prefer a particular alternative. That is, data where all respondents prefer CFLs to other choices will not lead to a successful estimation result. In such a case, the CFLs are said to *dominate* the other choices. The preliminary data meets both of conditions for the A-Lamp and Twister model and for the Reflector model. The model for Globes will likely require additional observations.

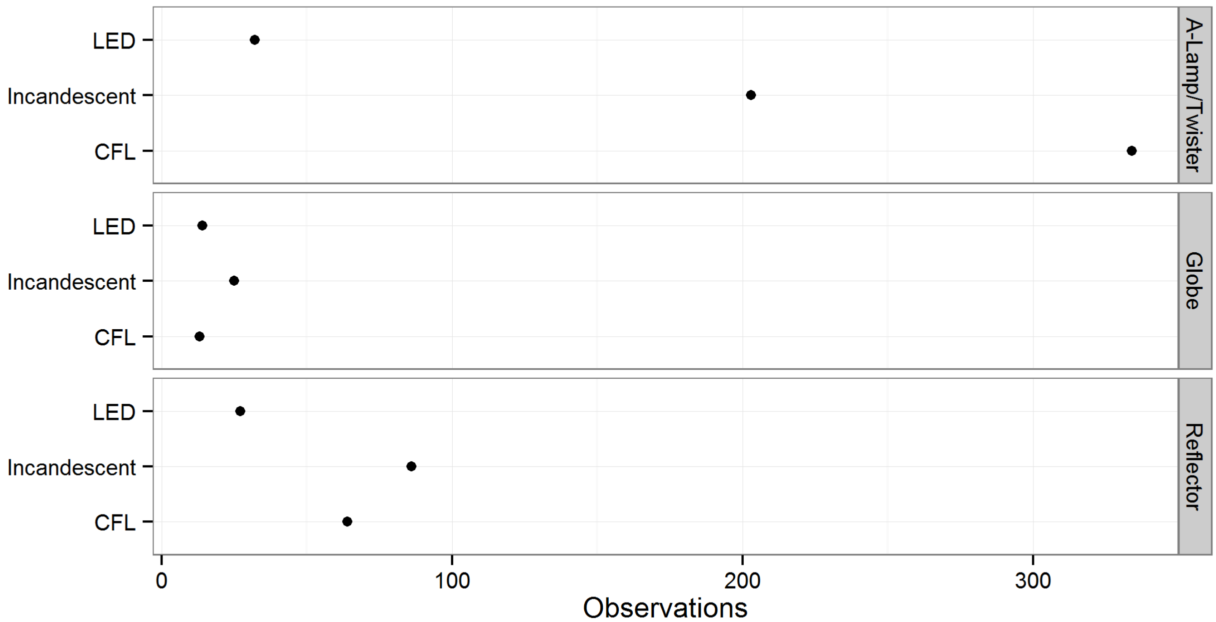

Figure 3. Observations by Preferred Lamp Style and Technology

Lamp Choice Model

Discrete choice models are useful for describing situations where the decision maker must choose an alternative rather than an amount. The goal of discrete choice modeling is to approximate how individuals value alternatives in the market. Discrete choice models represent the probability of an outcome as a response to variables that describe each of the possible outcomes. The models predict the probability for each possible alternative in a choice set for a decision maker.

Simulation techniques enable discrete choice models to estimate market shares. In a simulation framework, a researcher applies the discrete choice model over a representation of individuals in the market. The estimate of market shares is the aggregation of all individual results in the market. This facilities scenario testing—what happens if the prices of a particular lamp technology change—in ways that other techniques, such as conjoint analysis, do not allow. In other words, this technique leads to estimates of baseline and program market shares.

The remainder of this section describes building a model to estimate market shares. The section begins with a description the choice sets in the model. Unlike what consumers find in retail stores, the Lamp Choice Model generalizes lamps into a small number of alternatives. Next, the section outlines a general specification for a Lamp Choice Model. The general specific describes the types of variables that can help explain lamp choice. The section concludes with a discussion on nesting structures. Nesting structures define how consumers make substitutions between similar alternatives.

Choice Sets

The Lamp Choice Model design imposes some structure onto lamp choices to make this problem tractable. For example, we have ignored branding in the design of the preliminary Lamp Choice Model. Trying to predict consumer choice around branding adds complexity to the model without any benefit for program implementers. This subsection describes the generalizations of lamps into choice sets.

The Lamp Choice Model design calls for three separate logit models, one for each of the predominant lamp styles (A-Lamp and Twister, Reflector/Flood and Globe). As described above, choice sets should represent groups of alternatives that are reasonable substitutes. There are separate models by lamp style as lamps from one style are poor substitutes for lamps in another style. Within each choice set, the choice the consumer makes is which technology to buy.

Manufactures produce lamps in a myriad of wattages and brightness levels. To simplify these options into a discrete set of comparable alternatives, we grouped into lumen brightness bins, as shown in Table 1. These lumen brightness bins provide a useful framework for creating comparable choice sets for the experiment, even if consumers are not necessarily aware of lumens as a measure of brightness and manufacturers typically market lamps in terms of incandescent wattage equivalents.

Table 1. Lamp Brightness by Lamp Style

Lamp Brightness Category	*A-Lamp and Twisters*	*Reflectors/Floods*	*Globes*	*Three Ways*
Very High Brightness (>2099 lm*)	✔	✔		
High Brightness (1200 – 2099 lm)	✔	✔	✔	
Medium Brightness (700 – 1099 lm)	✔	✔	✔	
Low Brightness (65 – 699 lm)	✔	✔	✔	
Any Brightness				✔
Dimmable	✔	✔	✔	

* Lumens (lm)

The model design does not, however, allow for substitution across brightness bins. While consumers can and sometimes do replace a lamp in one brightness level with a lamp in another, the model design implicitly assumes that this is not the norm. Also, trying to incorporate substitution across brightness levels would impose additional difficulties in the intercept survey and would result in a more complex model design. The choice set would need account for lamp technology and lumen bin, expanding the number of alternatives by a factor of three.

The final aspect of the model choice sets relates to the retail channel. Not all lamps are available in each retail channel. Consumers in a discount store generally will not have the opportunity to purchase an LED A-Lamp for example. The model design reflects the difference in choice set by retail channel through availability restrictions that we developed from analysis of retail shelf surveys in 2012. The intercept survey presents only the choices a consumer is likely to see in the retail channel where the survey takes place. Likewise, the model estimation prohibits choices that are not available by retail channel.

General Specification

The particular form of discrete choice models shown in Equation (1) is the logit model. Logit models express the probability of the discrete choice *i* as the exponentiated *utility* of choice *i* over the sum of the exponentiated utilities of all choices.

$$\Pr(i) = \frac{\exp(U_i)}{\sum_{j \in J} \exp(U_j)} \tag{1}$$

Equation (2) gives the general specification for a utility equation that describes the value of a lamp. The final specification depends on an exploration of the intercept survey results and on the results from the model estimation.

$$\begin{aligned} U_j = \beta_{0,j} + \beta_{1,j} Price + \beta_{2,j} Watts + \beta_{3,j} RoomType + \beta_{4,j} FixtureType + \\ \beta_{5,j} Education + \beta_{6,j} RetailChannel \end{aligned} \tag{2}$$

where:
U_j is the utility of lamp technology j;
$\beta_{0,j}$ is the alternative specific constant for technology j;
β_1 to β_2 are the coefficients common to all technologies; and
$\beta_{3,j}$ to $\beta_{6,j}$ are the coefficients specific to technology j.

Note that since only the relative utility levels matter, the model sets the alternative specific constant for one of the alternatives to 0.

The design uses a common coefficient across the price and the wattage for each of the lamps. This reflects that consumers value these attributes independently from the technology. A price increase to one technology will have an equivalent effect to a price increase to an alternative technology. Likewise, the price of a watt-hour is constant. The technology differs in the amount of watts needed per hour of use. Note that the model specification cannot include both watts and lumens as these variables are highly collinear. Watts is a more attractive variable to include in the model. The coefficient on watts is effectively how much a consumer values future operating costs.

The remaining coefficients reflect variations among consumers and how consumers intend to use the lamp. For example, highly educated consumers may be more environmentally conscious or see investments in CFLs or LEDs as worthwhile given the energy savings and longer life benefits of these technologies. Similarly, consumers who plan to install a lamp in a closet or a basement may prefer incandescent lamps because they are relatively cheap and will not be used very often. The proposed model specification captures these effects through coefficients specific to the respondent's level of education and intended use/application for the lamp they purchased.

The model specification shown above does not address differences in price sensitivities due to income or other factors. This can be handled in one of two ways:

1. Create price sensitivity coefficients through segmentation.
2. Treat the coefficient on price as a random variable. This approach is known a random coefficient or mixed logit model. Latent class logit models are specific version of this approach.

The first approach is the conceptually and computationally easier approach. The second approach represents the price coefficient as a function of variable (e.g., income, occupants, and house structure). DNV KEMA has estimated both income segmented models and random coefficient models for this project.

Nesting Structure

The last element in the specification is a nesting structure. The structure of a multinomial logit models results in proportional substitution. This property is sometimes referred to as the red bus/blue effect. Say that travelers can chose between driving a car or a blue bus in one scenario. A second scenario adds a red bus that is identical to the blue bus in every way, except for the color. The multinomial logit model, shown in Figure 4 (a), shifts travelers from the car and the blue bus in equal proportions. That is, half of the new riders on the red bus will be former car drivers and half will be former blue bus riders. Clearly, this substitution pattern does not reflect that the busses are perfect substitutes for each other while the car is not as close a substitute.

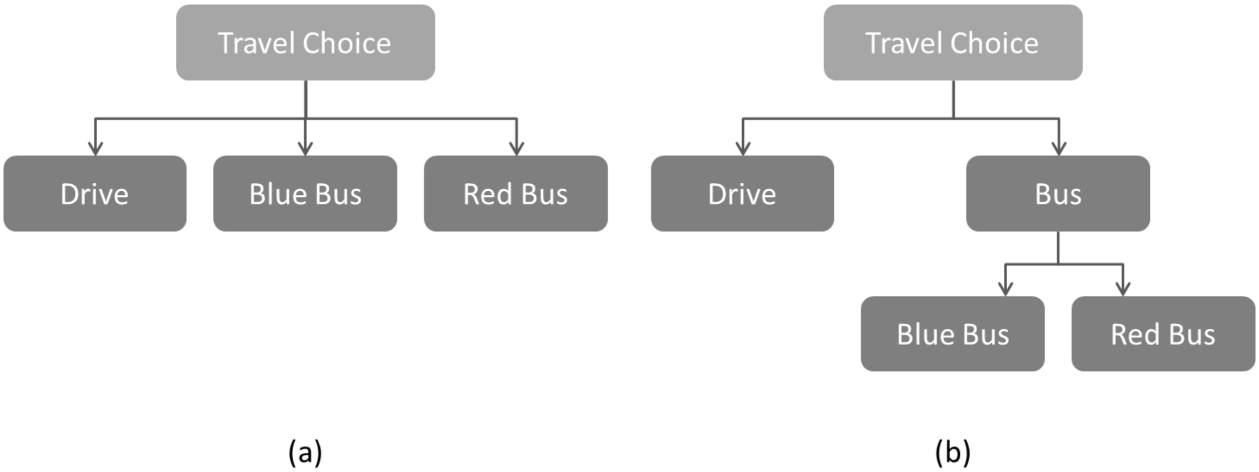

Figure 4. Example of a Nested Logit Structure

Figure 4 (b) shows an alternate logit model structure that treats the choice between the red and blue busses as a lower level choice than the choice between drive and bus. The term *nested logit* refers to a logit model where the probability of one group of alternatives is conditional on the probability of another alternative. The choice between red and blue busses is a logit model conditioned on the choice between drive and bus.

The nesting structure defines substitution patterns. Within the bus nest, decision makers see the red and blue busses as good substitutes. Increasing the frequency of the red bus will primarily have the effect of shifting riders from the blue bus to the red bus. The secondary effect will shift drivers to both busses.

Likewise, consumers do not substitute equally among lamp technologies. Figure 5 shows a proposed nesting structure. The nesting structure says that consumers view incandescent lamps differently than CFL and LED lamps. Increasing the price of traditional incandescent lamps will primarily shift consumer demand toward efficient incandescent lamps. As a secondary and lesser effect, consumers will also shift to CFL and LED technologies. Conversely, a sale on CFL twisters will pull more market share from CFL A-Lamps and LED lamps than from the two incandescent lamps.

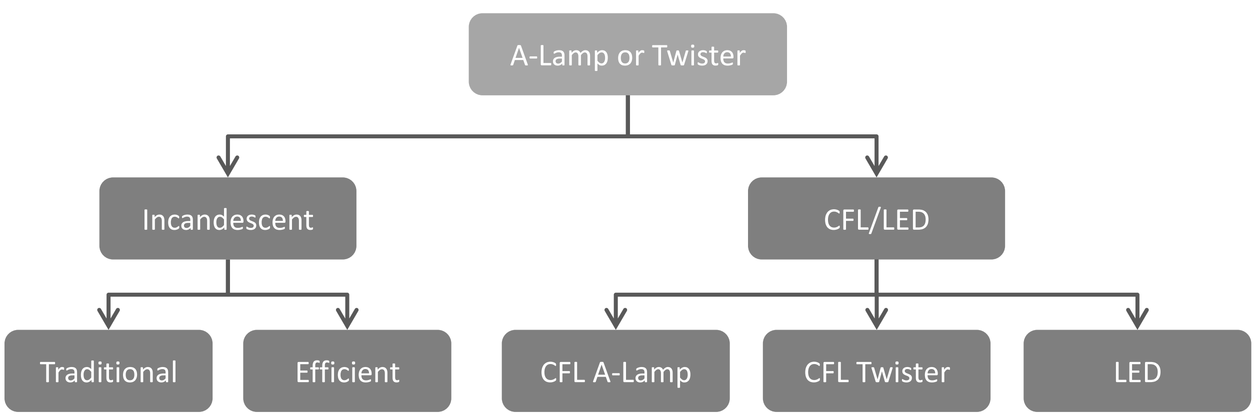

Figure 5. Preliminary Nesting Structure for Lamp Choice Model

Preliminary Findings

DNV KEMA is in the process of testing and refining the proposed model specification and nesting structure. The test for a satisfactory model is that it (1) produces statistically significant results and (2) tells a concise, consistent and coherent story. The first requirement ensures that model truly reflects the underlying data. The second ensures the model has only complexity necessary to reflect how consumers respond to market changes. The preliminary estimation results for the A-Lamp/Twister and Reflector models show the following relationships:

- **Higher income households.** Household with income of $100,000 per year or more place a premium on CFL and LED lamps. These lamps have a greater upfront cost but generate savings over time. The premium on LED lamps is greater than the premium on CFL lamps. Likewise, the LED lamps generate greater savings over time. This is a rational result for consumers willing to trade an upfront cost for a stream of savings over time and typical for higher income consumers.
- **Large home size.** Consumers in large homes (3 or more bedrooms) are less likely to purchase LED lamps, holding other factors constant. This may due to consumers wanting consistent lighting technology throughout a household. Investing in all LED lighting is significantly more expensive. Another possible explanation is that consumers living in larger homes have larger maintenance costs, which effectively reduces their income. Regardless, this finding needs to be further examined.
- **Renters.** Renters place less value on LED lamps than homeowners. Consumers that rent their homes may be less likely to purchase more expensive, long-lasting LED lamps if they expect to change homes before the full benefit of those investments are realized.
- **Highly educated consumers.** As suggested above, highly educated consumers are more likely to purchase LED lamps. These consumers may be more sensitive to environmental issues or better recognize the long term savings potential of LED lamps.
- **A-Lamps and Twisters versus Reflectors.** Consumers are more price sensitive when purchasing A-Lamps and Twisters compared to Reflectors. This result implies that consumers place more emphasis on the non-price characteristics of Reflectors compared to A-Lamps and Twisters.
- **Watts as an explanatory variable.** Including watts as an explanatory variable is difficult. There is a clear ordering between the nominal wattage of LED, CFL, and incandescent lamps. That is, incandescent lamps always use more watts than CFLs and CFLs always use more watts than LEDs. This prevents the estimator untangling the true effect of wattage. Instead, the estimator places the savings due to less energy usage in the alternative-specific constant for the alternative.

The complete estimation results are under review and not yet publically available. Further, there are ongoing data collection efforts that will approximately double the number of observations. The additional data are particularly helpful for globe and three-way lamps, which are less frequently observed than other styles.

Conclusions

The intercept survey and Lamp Choice Model design both recognize the ongoing transformation within the residential lighting market. The guiding principle behind the survey and the model is that measuring and modeling the residential lighting market needs to transform as well. This market is complex and simple price elasticities are not sufficient for explaining choices in this market. DNV KEMA has responded to this transformed market with two innovations:

- **Dynamic intercept survey instrument.** We have successfully deployed a survey instrument that is able to capture consumer preferences toward lighting products. The survey instrument is able to adapt a preference ranking experiment to the contents of a respondents shopping basket. Further, the instrument is able to vary the prices in the experiment based on underlying data that represents reasonable alternative choice sets. This leads to more robust data for choice modeling and would have been impossible using standard, paper data collection techniques.
- **Choice models for lighting markets.** This paper outlines an approach to understanding the residential lighting market that begins with individuals making choices. We are developing these models using data from consumers making real-world choices. This gives us confidence that the models will closely mimic the decision process of real-world consumers. Further, we are able to capture the intended application of the lamps. This gives greater insight into where lamp technologies are installed. We are actively refining the Lamp Choice Model to be sensitive to this effect.

Lighting is no longer a textbook example for price elasticities. However, this paper describes the techniques program planners and evaluators can use to understand the dynamics of this changing market.