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Analysis

# Labeling energy cost on light bulbs lowers implicit discount rates

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ABSTRACT

Lighting accounts for nearly 20% of overall U.S. electricity consumption and 18% of U.S. residential electricity consumption. A transition to alternative energy-efficient technologies could reduce this energy consumption considerably. To quantify the influence of factors that drive consumer choices for light bulbs, we conducted a choice-based conjoint field experiment with 183 participants. We estimated discrete choice models from the data, and found that politically liberal consumers have a stronger preference for compact fluorescent lighting technology and for low energy consumption. Greater willingness to pay for lower energy consumption and longer life was observed in conditions where estimated operating cost information was provided. Providing estimated annual cost information to consumers reduced their implicit discount rate by a factor of five, lowering barriers to adoption of energy efficient alternatives with higher up-front costs; however, even with cost information provided, consumers continued to use implicit discount rates of around 100%, which is larger than that experienced for other energy technologies.



## 1. Introduction

In 2008, residential compact fluorescent lamp (CFL) socket saturation[1] was 10% nationwide (D&R International, Ltd., 2009), with the remainder being almost entirely incandescent bulbs. About half of the total lighting service (in terms of lumens) was provided by incandescent bulbs, and a little over 20% was provided by CFL bulbs (Navigant Consulting, 2010), suggesting that further adoption of CFLs – or other efficient lighting technologies, such as light emitting diodes – could achieve considerable energy savings in the residential sector. In many cases, these efficient alternatives would also save money for households. The slow transition to CFLs does not seem to be due to poor public awareness, since about 70% of Americans know about CFLs (Sylvania, 2010). These data suggest that there may be other barriers that keep consumers from adopting CFLs.

Engineering economic analyses have long suggested that there is a gap between current residential energy consumption and optimal levels that could be achieved if the most energy-efficient and cost-effective end-use technologies providing the same level of energy services were adopted instead (Hirst and Brown, 1990; Jaffe and Stavins, 1994). There have been numerous studies analyzing potential reasons that prevent optimal efficiency from being achieved (Anderson and Claxton, 1982; Brown, 2001; Golove and Eto, 1996), including low price of energy caused by distortional regulation, misplaced incentives between tenants and landlords (also known as the principal-agent problem), lack of access to financing options (Blumstein et al., 1980), uncertainty in the future price of electricity or other fuels, low priority of energy issues for consumers among other types of expenditures (Brown, 2001), consumers' limited cognitive capacity (Anderson and Claxton, 1982), and the fact that energy efficiency often is inseparable from other unwanted features in products (Golove and Eto, 1996). A recent report from the National Acedemies of Science (2009) states that well-designed policies such as building energy codes, Energy Star product labeling, and efficiency standards could help overcome these barriers and that these policy initiatives already achieve primary energy savings of about 13 quadrillion BTU per year.

Researchers have taken various approaches to measure the relative priority consumers place on energy efficiency versus upfront cost when making technology purchases, including implicit discount rates (IDRs) (Gately, 1980; Meier and Whittier, 1983). The IDR, or hurdle rate, is the value of the discount rate for a hypothetical net-present-value-maximizing consumer that best matches observed choice behavior. When viewed from the framing of classical economic discounting, consumers appear to behave as though they are using the implicit discount rate to value current vs. future costs (with some error).

The IDRs are used as inputs in many energy-economy models to explain how the share of end-use energy technologies evolves over time. For example, the Energy Information Agency's (EIA) National Energy Modeling Systems (NEMS), assumes hurdle rates for consumer appliances that range from 15% (gas furnace) to 90% (electric clothes dryer) depending on the residential end-uses considered (U.S. EIA,

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[1] Socket saturation is frequently used as a measure of market penetration of a specific type of light bulb. It is defined as a percentage of total number of bulb sockets that contain a specific type of light bulb.

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2011). There are debates on the usefulness and appropriate ranges of such estimates of IDRs as a means of describing consumer choices and behavior (Frederick et al., 2002). Attributing consumers' choices solely to their discount rates can lead to misunderstanding consumer behavior, since other factors such as the effect of marketing and advertising, lack of knowledge, or imperfect substitutability across two competing technologies also play a role in choices (Mulder, 2005). However, in terms of energy system modeling, using high discount rates to explain technology choices by consumers is still the standard approach.

To improve understanding of barriers to adoption of energy-efficient lighting, we perform choice-based conjoint experiments and assess the following:

1. We measure consumer preferences and willingness to pay (WTP) for general illumination, and we identify barriers to the adoption of efficient lighting technologies. Specifically, we quantify the importance of product attributes (price, wattage, brightness, lifetime, and technology type) and consumer characteristics (income, education, housing characteristics, political views, perception of climate change, and perception of toxicity issues) in determining bulb choice. Using WTP allows us to directly compare preferences for distinct attributes that have different units.
2. We estimate IDRs for lighting technologies.
3. The Federal Trade Commission (FTC) implemented a new label that includes estimated operation cost information and is required on lamp packages starting in 2012. We measure the effect of labeling estimated bulb operation cost on resulting choices, WTP, and IDRs.

In the next section, we summarize the literature on IDRs and discrete choice analysis. Based on this understanding, the method and the results of our experiment will be explained in Sections 3 and 4 respectively, and in Section 5 we conclude.

## 2. Previous Work on Eliciting Implicit Discount Rates for Energy-Saving Household Appliances

Research on consumers' IDRs started in the 1980s using two general methods: 1) asking participants hypothetical questions about the future savings they would require before making investments in energy efficiency (see, for example, Houston, 1983), and more commonly, 2) building econometric models of consumer utility or other quantities and comparing coefficients for price and/or annual operating cost variables. The second method can implicitly derive discount rates without forcing participants to answer speculative questions like the first method does. We use a variant of this second method with a nonlinear model specification explained in the next section.

Table 1 provides a summary of several studies that elicited IDR for end-use energy technologies over time. We provide more detail regarding the study from Hausman (1979), who constructed an individual choice model for air conditioners (AC), as it has the closest formulation to our model. In this model, each individual chooses a specific AC that maximizes his or her utility function. The utility function posed is:

$$U_j = -\beta_1 \cdot OCost_j - \beta_2 \cdot Price_j - \beta_3 \cdot Discomfort_j + \varepsilon_j, \tag{1}$$

where $U_j$ is the utility gained by selecting product $j$, $OCost_j$ is the annual electricity cost ($/year) due to AC use, $Price_j$ is the initial purchase cost ($), $Discomfort_j$ is the discomfort level that increases as the temperature setting for the AC increases, and $\varepsilon_j$ is the error term. From purchase records and capacity/efficiency information of ACs in the market, Hausman estimated the coefficients in the utility function using maximum likelihood estimation. The author assumes that the utility depends on annualized capital cost, so that $\beta_2$ is an annualizing factor. Then, the implicit discount rate $r$ can be computed using the capital recovery factor for a given AC lifetime $q$:

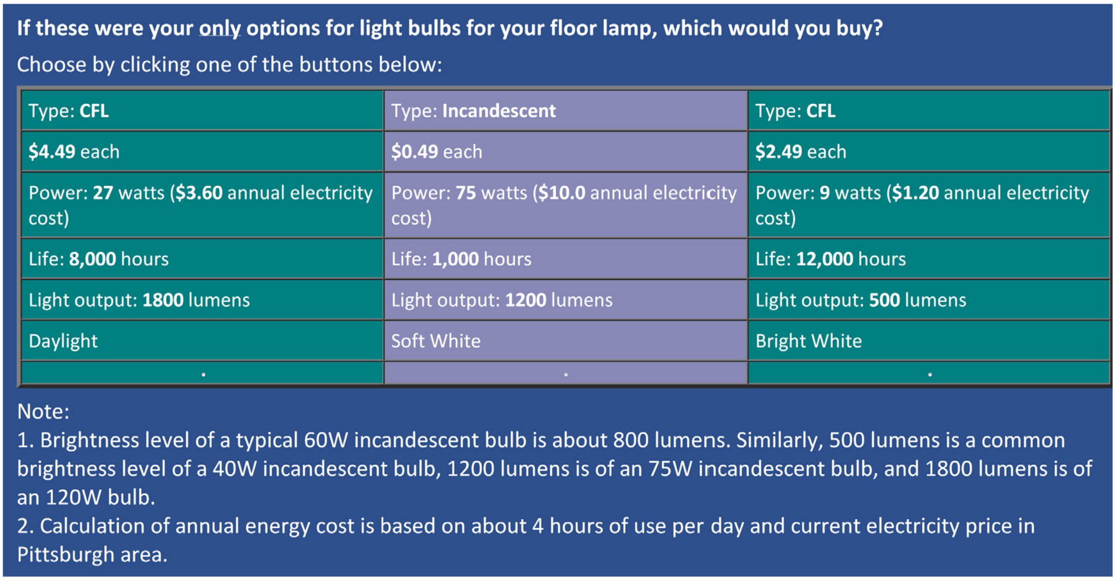
$$\hat{\beta}_2 = \hat{\beta}_1 \frac{r(1+r)^q}{(1+r)^q - 1}. \tag{2}$$

The resulting IDRs in the study ranged from 5% to 89% depending on household income level.

Frederick et al. (2002) emphasize that the intertemporal choices, such as investments in energy-efficiency, are not only influenced by time preferences – what they define as "the preference for immediate utility over delayed utility" – which we measure with IDRs. Rather, they are determined jointly by various confounding factors such as

**Table 1**
Selective reviews of studies on implicit discount rate implied by purchases of energy efficient goods.

| Study | Product | Data source | Year of data retrieval | Range of estimated discount rate | Method |
|---|---|---|---|---|---|
| Hausman (1979) | Room AC | 46 samples from an MRI energy consumption survey and AHAM product directory | 1978 | 5.1% ~ 89% (with income effect added) | Econometric model (discrete choice analysis) |
| Gately (1980) | 17 cu-ft. refrigerator | Price data of models from three major manufacturers | Jan 1978 | 45% ~ 300% | Unspecified |
| Houston (1983) | Hypothetical device | Mail survey (1081 samples from Indiana) | 1979 | 10% ~ 50% (given as choices in the survey): with mean of 22.5% | Direct inquiry |
| Meier and Whittier (1983) | 17 cu-ft. refrigerator | Price data from a nationwide retailer | 1977–1979 | 1% ~ 102% | Price and energy use comparison |
| Dreyfus and Viscusi (1995) | Automobile | Residential Transportation Energy Consumption Survey by DOE (1775 observations) | 1988 | 11% ~ 17% | Econometric model (Nonlinear least square) |
| Ruderman et al. (1987) | Heating and cooling equipment, refrigerator | Appliance purchase cost and efficiency data from DOE and other reports, and historical shipping data from DOE | 1972–1980 | 18% ~ 825% | Lifecycle cost minimization |
| Doane and Hartman (1984) | Thermal shell, window and door, water heating, space heating | Customer energy use survey by an utility (GPU, now FirstEnergy) (882 households), cost and savings estimates from Lawrence Berkeley Natl lab | 1982 | 0% ~ 400% | Econometric model (discrete choice analysis) |
| Mau et al. (2008) | Hybrid electric car and hydrogen fuel cell vehicles | Mail survey (916 for HEV, 1019 for HFCV) | 2002 | 21% ~ 49% | Controlled experiment (discrete choice analysis) |
| This study | Light bulbs | Choice-based conjoint experiment with 183 participants | 2011 | Explained below | Controlled experiment (discrete choice analysis) |



**If these were your only options for light bulbs for your floor lamp, which would you buy?**
Choose by clicking one of the buttons below:

| | | |
|---|---|---|
| Type: **CFL** | Type: **Incandescent** | Type: **CFL** |
| **$4.49** each | **$0.49** each | **$2.49** each |
| Power: **27** watts (**$3.60** annual electricity cost) | Power: **75** watts (**$10.0** annual electricity cost) | Power: **9** watts (**$1.20** annual electricity cost) |
| Life: **8,000** hours | Life: **1,000** hours | Life: **12,000** hours |
| Light output: **1800** lumens | Light output: **1200** lumens | Light output: **500** lumens |
| Daylight | Soft White | Bright White |

Note:
1. Brightness level of a typical 60W incandescent bulb is about 800 lumens. Similarly, 500 lumens is a common brightness level of a 40W incandescent bulb, 1200 lumens is of an 75W incandescent bulb, and 1800 lumens is of an 120W bulb.
2. Calculation of annual energy cost is based on about 4 hours of use per day and current electricity price in Pittsburgh area.

**Fig. 1.** Example of a choice task seen by participants. The attribute values in the table change in each choice task following our randomized design. Each subject answered 15 tasks similar to this one on a laptop. The annual operating cost in parentheses in the third row of the table was shown only to half of the participants.

intertemporal arbitrage (e.g. imperfect capital markets), uncertainty (i.e. uncertain about whether future energy savings will be achieved), and expectations of changing utility functions (e.g. expecting increased future income or wealth). Azevedo et al. (2009) and Jaffe and Stavins (1994) also argued that IDRs include factors such as lack of technical or financial knowledge, the role of marketing or advertising, or habit formation. Despite this caveat, our estimation of IDRs for the lighting sector will contribute to a better understanding of the energy efficiency gap regarding the adoption of energy-efficient lighting.

## 3. Methods

### 3.1. Experimental Method

We observe choices made by participants in an experiment and construct an econometric model of consumer utility as explained later in Section 3.2. In preparation for this study, we conducted preparatory pilots and interviews and found the five most important bulb characteristics for consumers were price, energy use, color, lifetime, and brightness. Some participants also mentioned bulb startup time, headaches, and dimming as potential impeding factors for CFLs. Although there is no scientific evidence that CFLs cause headaches (U.S. FDA., 2012), we included health questions in our questionnaire because these reported subjective perceptions can also influence choices.

The field experiment consisted of three main parts: 1) a conjoint choice experiment, 2) choices of real light bulbs, and 3) questions on demographics, experience, knowledge, and attitudes. To observe the effect of disclosing annual cost information, subjects were randomly assigned to either one of two groups. Half of the participants were shown annual operating cost information in their choice tasks while the other half were not. From this point, the group provided with the information is referred to as the *with-cost* group and the group without it as the *without-cost* group.

#### 3.1.1. Experiment Setup

We designed a controlled experiment with a choice based conjoint survey. The stated choices are then used to estimate several random utility discrete choice models. The experiment was performed in a mobile laboratory,[2] using laptops set up with choice tasks (using Sawtooth software) and a survey.[3] We asked a total of 39 questions (15 choice tasks + 24 additional questions). Each choice task presented three alternatives among which a participant chooses one, as shown in Fig. 1.

The attribute levels were selected to cover the ranges commonly available in the market, and product profiles were selected from the full factorial of $2 \times 3^5$ potential permutations. For each subject, 36 alternatives (12 tasks/subject $\times$ 3 alternatives/task) were generated using Sawtooth's complete enumeration strategy, which seeks to achieve balance and orthogonality for main effects and first order interactions while minimizing overlap among attribute levels within each choice task (Kuhfeld, 1997). Many of the profiles represent combinations of attributes that do not appear together for products in today's market (e.g.: 75 W CFL with a 1000 hour lifetime), but all represent plausible and understandable alternatives, and the enumeration allows elimination of sources of bias like multi-collinearity.

Three fixed choice tasks were identical for all participants. The role of the first two fixed tasks was intended to check whether participants are paying attention to the experiment. In the first fixed task, the alternatives are identical except that one has a longer life than the others. In the second one, one alternative had the lowest price and the longest life. Fifteen subjects out of 183 who did not choose the dominant alternatives in these two tasks were considered as not attentive and removed from our analysis.

The third fixed task was used to determine the compensation to participants (hereinafter referred to as "compensation task"). Jointly with the consent form, participants were given an instruction page where it was stated: "Your choice from one specific question, placed randomly among the fifteen choice questions you will answer, determines the compensation you will receive at the end of the experiment." Thus, one among the three types of real light bulbs was handed out to participants at the end of the experiment depending on their choices from the compensation task. Participants were informed beforehand that they

[2] The Center for Behavioral and Decision Research (http://www.cbdr.cmu.edu/datatruck/index.html).

[3] Sawtooth is a software commonly used for marketing studies and conjoint analyses (http://www.sawtoothsoftware.com/).

would be compensated with a type of light bulb decided based on their choices, but they were not told which specific task determined the compensation. Ding et al. (2005) tested adding an incentive among the conjoint choice tasks and observed that this method helps participants to make choices that are closer to their true preference, reducing the limitation of observing stated preferences that differ from market behavior, although the compensation may have also incentivized people who might otherwise have chosen lower priced bulbs to choose the expensive bulbs, which would lead to somewhat deflated price coefficients.

#### 3.1.2. Physical Choice Task

Once the computer-based choice tasks were finalized, participants were asked to follow the experimenter to another room, where they were asked to choose among five pairs of real light bulbs in their original packaging. Price information was provided on a tag next to each lamp package. These choices were not used as compensation to participants; these choices were simply used to compare physical light bulb choices with the predictions from our model to assess external validity.

#### 3.1.3. Demographics, Experience, Knowledge, and Attitudes

After the choice tasks, each participant was asked to fill out a survey with questions on demographics, prior experience with lamps, environmental attitudes, political views, basic understanding of bulb characteristics, perception of climate change, and perception of toxicity issues.

### 3.2. Analytical Model

#### 3.2.1. Consumer Utility Model

We estimate a mixed logit model, which models heterogeneity of consumer preferences via random coefficients and mitigates the restrictive substitution patterns (i.e. independence of irrelevant alternatives (IIA)) of a multinomial logit (MNL) model and improves fit.[4] Logit estimates using categorical variables for all attributes (discrete conjoint levels) suggest linear or quadratic utility functions for numerical explanatory variables (price, brightness, power, and lifetime), and we use these throughout.[5] The utility $U_{ij}$ that consumer $i$ draws from product alternative $j$ is modeled as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \sum_{k=1}^{K}\left(\beta_k \cdot x_{jk} + \sum_{n=1}^{N}\gamma_{kn} \cdot z_{in} \cdot x_{jk}\right) + \varepsilon_{ij}, \tag{3}$$

where $\beta_k$ is the preference coefficient for attribute $k$, $x_{jk}$ is the $k$-th attribute of alternative $j$, $\gamma_{kn}$ is the coefficient for interactions between consumer attribute $n$ and product attribute $k$, $z_{in}$ is the $n$-th attribute of consumer $i$, and $\varepsilon_{ij}$ is the random error term, taken as an iid standard Gumbel distribution (Train, 2003). The interaction terms $z_{in} \cdot x_{jk}$ reveal how individual characteristics can affect preference for bulb attributes. We assume continuous numerical bulb attributes unless otherwise noted, as shown in Table 2. For the mixed logit model, both $\beta_k$ and $\gamma_{kn}$ are random variables, assumed to be normally or log-normally distributed with distributional parameters estimated via likelihood maximization.

Specifically, our base model (Model 2 in Table 3), which excludes respondent covariates $z_{in}$, is:

$$\begin{aligned} U_{ij} = {} & (\overline{\beta}_1 + \sigma_1\nu_{1i})x_j^{\mathrm{TYPE}} - \exp(\overline{\beta}_2 + \sigma_2\nu_{2i})x_j^{\mathrm{PRICE}} + \exp(\overline{\beta}_3 + \sigma_3\nu_{3i})x_j^{\mathrm{LIFE}} \\ & + (\overline{\beta}_4 + \sigma_4\nu_{4i})x_j^{\mathrm{BRIGHT}} + (\overline{\beta}_5 + \sigma_5\nu_{5i})\left(x_j^{\mathrm{BRIGHT}}\right)^2 + (\overline{\beta}_6 + \sigma_6\nu_{6i})x_j^{\mathrm{WATT}} \\ & + \textstyle\sum_{m=1}^{2}(\overline{\beta}_{7m} + \sigma_{7m}\nu_{7mi})x_{mj}^{\mathrm{COLOR}} \\ & + D_i^{\mathrm{OPCOST}}(\overline{\beta}_1^{\mathrm{C}}x_j^{\mathrm{TYPE}} + \overline{\beta}_2^{\mathrm{C}}x_j^{\mathrm{PRICE}} + \overline{\beta}_3^{\mathrm{C}}x_j^{\mathrm{LIFE}} + \overline{\beta}_4^{\mathrm{C}}x_j^{\mathrm{BRIGHT}} + \overline{\beta}_5^{\mathrm{C}}\left(x_j^{\mathrm{BRIGHT}}\right)^2 \\ & + \overline{\beta}_6^{\mathrm{C}}x_j^{\mathrm{WATT}} + \textstyle\sum_{m=1}^{2}\overline{\beta}_{7m}^{\mathrm{C}}x_{mj}^{\mathrm{COLOR}}) + \varepsilon_{ij}, \end{aligned} \tag{4}$$

where $m$ indexes the discrete levels of the color attribute, $\overline{\beta}$ and $\sigma$ are the distributional parameters for the random coefficients, and $\nu$ is a random variable with an iid standard normal distribution. We assume that preference for type, brightness, and wattage varies normally in the population and preference for price and life varies log-normally, since a change in sign for preference of price or life would be counterintuitive and theoretically problematic. For interaction terms, we use fixed coefficients for ease of interpretation. In our final model (Model 3 in Table 3), we test the interaction between lifetime and income levels, which was the only significant interaction term in several variants of the model we tested. Other interactions between bulb types and perception/attitude variables are included to understand whether consumers would differ in their choices for incandescent or fluorescent technologies as a result of their perceptions or attitudes toward climate change, toxicity associated with certain lighting technologies, participants' awareness of the relationships between bulb characteristics, and participants' political orientation.

#### 3.2.2. Model for Estimation of Implicit Discount Rates

To estimate IDRs, many conventional studies including Hausman's (1979) assumed a single exogenous value of average lifetime. This assumption was inappropriate in our case considering our use of lifetime as an independent variable determining consumer utility and also the vast difference between a lifetime of a CFL and that of an incandescent

**Table 2**
Descriptions of variables.

| Variable | Description | Value |
|---|---|---|
| $x_{ij}^{\mathrm{TYPE}}$ | Dummy indicating bulb type | 0: incandescent, 1: CFL |
| $x_{ij}^{\mathrm{PRICE}}$ | Price of the bulb $j$ in subject $i$'s choice task | \$0.49/\$2.49/\$4.49 |
| $x_{mij}^{\mathrm{COLOR}}$ | Dummy for color, where $x_{1ij}^{color}$ is bright white and $x_{2ij}^{color}$ is daylight | 0: No, 1: Yes |
| $x_{ij}^{\mathrm{LIFE}}$ | Lifetime of the bulb $j$ in subject $i$'s choice task | 1000/8000/12,000 [hours] |
| $x_{ij}^{\mathrm{BRIGHT}}$ | Brightness level of the bulb $j$ in subject $i$'s choice task | 500/1200/1800 [lumens] |
| $x_{ij}^{\mathrm{WATT}}$ | Power consumption of the bulb $j$ in subject $i$'s choice task | 9/25/75 [watt] |
| $D_i^{\mathrm{OPCOST}}$ | Dummy indicating whether annual operating cost information is provided to subject $i$ | 0: No, 1: Yes |
| $z_i^{\mathrm{EXPERIENCE}}$ | Dummy indicating whether subject $i$ has used CFLs before | 0: No, 1: Yes |
| $z_i^{\mathrm{BUYBULB}}$ | Dummy indicating whether subject $i$ buys light bulbs sometimes | 0: No, 1: Yes |
| $z_i^{\mathrm{HEALTH}}$ | Dummy indicating whether subject $i$ has experienced any health issues related to CFL use | 0: No, 1: Yes |
| $z_i^{\mathrm{BACHELOR}}$ | Dummy indicating whether subject $i$ has a bachelor's degree | 0: No, 1: Yes |
| $z_i^{\mathrm{MIDINC}}$ $z_i^{\mathrm{HIINC}}$ | Dummy indicating subject $i$'s annual household income, where mid-income is between \$30 k and \$75 k and high-income is above \$75 k | 0: No, 1: Yes |
| $z_i^{\mathrm{TOXICCFL}}$ | Dummy indicating whether the subject believes only CFLs contain toxic materials | 0: No, 1: Yes |
| $z_i^{\mathrm{TOXICBOTH}}$ | Dummy indicating whether the subject believes both bulbs contain toxic materials | 0: No, 1: Yes |
| $z_i^{\mathrm{TOXIC,k}}$ | Dummy indicating whether subject $i$'s belief of seriousness of toxicity issue related to light bulbs is in category k (base = not at all serious, k = not very serious/somewhat serious/very serious/not aware) | 0: No, 1: Yes |
| $z_i^{\mathrm{KNOWLEDGE}}$ | Number of correct answers among the four questions regarding basic lighting technology | 0–4 |
| $z_i^{\mathrm{CC,k}}$ | Dummy indicating whether subject $i$'s belief of seriousness of climate change is in category k (base = not at all serious, k = not very serious/somewhat serious/very serious/not aware) | 0: No, 1: Yes |
| $z_i^{\mathrm{LIBERAL}}$ | Dummy indicating whether the subject is politically liberal | 0: No, 1: Yes |

[4] A likelihood ratio test between a MNL model and our basic mixed logit model gives $\chi^2(8) = 457.1$ and p <0.001 (Model 1 and Model 2 in Table 3).

[5] Additional results for alternative model specifications are available from the authors upon request.

**Table 3**
Main results.

| | Variables | Model 1 | | Model 2 | | | | Model 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $\overline{\beta}$ | | $\overline{\beta}$ | | $\sigma$ | | $\overline{\beta}$ | | $\sigma$ | |
| Main effects of bulb attributes | CCT = 5000K | 0.00369 | (0.0774) | −0.00439 | (0.130) | 0.771 | (0.0858)*** | −0.0103 | (0.130) | 0.805 | (0.0899)*** |
| | Type = CFL | 0.434 | (0.0689)*** | 0.571 | (0.136)*** | 1.110 | (0.101)*** | 0.227 | (0.537) | 1.070 | (0.103)*** |
| | Watt | −0.00229 | (0.00117)* | −0.00310 | (0.00220) | 0.0161 | (0.00161)*** | 0.00724 | (0.00918) | 0.0162 | (0.00171)*** |
| | Brightness(×10^3 lm) | 1.373 | (0.374)*** | 2.200 | (0.470)*** | 0.619 | (0.145)*** | 2.190 | (0.473)*** | 0.654 | (0.128)*** |
| | Brightness^2 | −0.478 | (0.159)*** | −0.839 | (0.200)*** | 0.195 | (0.0659)*** | −0.836 | (0.201)*** | 0.188 | (0.0569)*** |
| | Life(×10^3 h) (log-normal) | 0.0603 | (0.00748)*** | −2.655 | (0.184)*** | 0.916 | (0.122)*** | −2.845 | (0.255)*** | 1.070 | (0.177)*** |
| | Price (log-normal) | −0.151 | (0.0200)*** | −2.231 | (0.240)*** | 1.438 | (0.149)*** | −2.198 | (0.245)*** | 1.414 | (0.148)*** |
| Effect of providing annual operating cost info | (CCT = 3700K) ∗ Dopcost | 0.138 | (0.114) | 0.0788 | (0.169) | | | 0.0792 | (0.169) | | |
| | (CCT = 5000K) ∗ Dopcost | 0.128 | (0.111) | 0.197 | (0.179) | | | 0.233 | (0.181) | | |
| | Watt ∗ Dopcost | −0.00674 | (0.00171)*** | −0.0100 | (0.00303)*** | | | −0.0123 | (0.00308)*** | | |
| | Life ∗ Dopcost | 0.0293 | (0.0108)*** | 0.0292 | (0.0156)* | | | 0.0320 | (0.0151)** | | |
| | Brightness ∗ Dopcost | −0.161 | (0.533) | −0.216 | (0.656) | | | −0.218 | (0.663) | | |
| | Brightness^2 ∗ Dopcost | 0.0437 | (0.228) | 0.0856 | (0.279) | | | 0.0988 | (0.281) | | |
| | (Type = CFL) ∗ Dopcost | −0.148 | (0.0989) | −0.164 | (0.187) | | | −0.0337 | (0.190) | | |
| | Price ∗ Dopcost | 0.0147 | (0.0284) | −0.00270 | (0.0366) | | | 0.00749 | (0.0377) | | |
| Interaction effects of consumer attributes | Life ∗ High-income | | | | | | | 0.0357 | (0.0196)* | | |
| | Life ∗ Mid-income | | | | | | | 0.00139 | (0.0169) | | |
| | (Type = CFL) ∗ (CC = not very serious) | | | | | | | 0.652 | (0.543) | | |
| | (Type = CFL) ∗ (CC = somewhat serious) | | | | | | | 0.185 | (0.444) | | |
| | (Type = CFL) ∗ (CC = very serious) | | | | | | | 0.426 | (0.418) | | |
| | (Type = CFL) ∗ (CC = not aware) | | | | | | | −0.0639 | (0.756) | | |
| | Watt ∗ (CC = not very serious) | | | | | | | −0.00447 | (0.00859) | | |
| | Watt ∗ (CC = somewhat serious) | | | | | | | 0.000507 | (0.00740) | | |
| | Watt ∗ (CC = very serious) | | | | | | | −0.00275 | (0.00711) | | |
| | Watt ∗ (CC = not aware) | | | | | | | −0.0174 | (0.0136) | | |
| | (Type = CFL) ∗ (Toxic in CFL) ∗ (Toxic = not very dangerous) | | | | | | | −0.347 | (0.360) | | |
| | (Type = CFL) ∗ (Toxic in CFL) ∗ (Toxic = somewhat dangerous) | | | | | | | 0.506 | (0.332) | | |
| | (Type = CFL) ∗ (Toxic in CFL) ∗ (Toxic = very dangerous) | | | | | | | −0.806 | (0.480)* | | |
| | (Type = CFL) ∗ (Toxic in CFL) ∗ (Toxic = not aware) | | | | | | | −0.870 | (0.810) | | |
| | (Type = CFL) ∗ Knowledge | | | | | | | −0.0518 | (0.0897) | | |
| | Watt ∗ Knowledge | | | | | | | −0.000954 | (0.00147) | | |
| | (Type = CFL) ∗ Liberal | | | | | | | 0.370 | (0.200)* | | |
| | Watt ∗ Liberal | | | | | | | −0.00746 | (0.00329)** | | |
| | Observations | 6552 | | 6552 | | | | 6552 | | | |
| | Log-likelihood | −2164 | | −1936 | | | | −1921 | | | |
| | AIC/BIC | 4361/4470 | | 3920/4083 | | | | 3925/4210 | | | |

Standard errors in parentheses.
*** $p < 0.01$
** $p < 0.05$
* $p < 0.1$

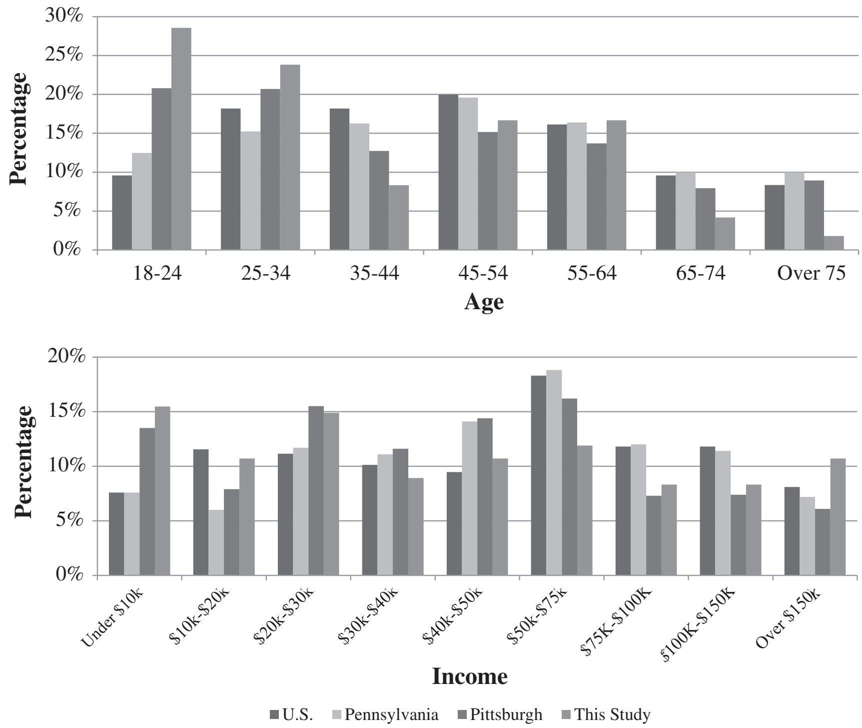



**Fig. 2.** Distributions of age and income (N = 168). City and state data are from the 2010 U.S. Census (U.S. Census Bureau, 2010).

bulb in the market. Instead, we estimated the IDR explicitly in the estimation procedure using annualized cost:

$$(\text{annualized capital cost}) = \frac{r(1+r)^{x^{\text{LIFE}}}}{(1+r)^{x^{\text{LIFE}}}-1} \cdot x^{\text{PRICE}}. \tag{5}$$

Here, $x^{\text{LIFE}}$ is expressed in years.[6] The base model specification for estimating IDR is

$$U_{ij} = -exp(\beta_0 + \sigma_0 \nu_{0i}) \left( \frac{\beta_1 (1+\beta_1)^{x_{ij}^{\text{LIFE}}}}{(1+\beta_1)^{x_{ij}^{\text{LIFE}}}-1} x_{ij}^{\text{PRICE}} + x_{ij}^{\text{OPCOST}} \right) + (\beta_2 + \sigma_2 \nu_{2i}) x_{ij}^{\text{TYPE}} \\ + (\beta_3 + \sigma_3 \nu_{3i}) x_{ij}^{\text{BRIGHT}} + (\beta_4 + \sigma_4 \nu_{4i}) \left( x_{ij}^{\text{BRIGHT}} \right)^2 + \sum_{m=1}^{2} (\beta_{5m} + \sigma_{5m} \nu_{5mi}) x_{mij}^{\text{COLOR}} + {}_{ij}, \tag{6}$$

where $\beta_0$ represents the average consumer sensitivity to annualized cost of ownership and $\beta_1$ represents the consumer's IDR. Other $\beta$s can be interpreted in the same way as in Eq. (4).[7] [8] Because the conjoint task is randomized, the estimate of IDR should be independent of the presence of other attributes in the model. Through maximum likelihood estimation, we can estimate the population's average IDR (i.e. $\hat{\beta}_1$ ) employed when making purchasing decisions for any lighting products.

[6] We assume that consumers accept the lifetime information written on packages as true, i.e. they do not anticipate an early failure or a defective bulb.

[7] Because the IDR model is nonlinear in parameters, the log-likelihood function may have multiple local maxima. We seek global maxima via randomized multistart.

[8] Wattage is perfectly correlated with operating cost, so their effects cannot be determined independently. By removing wattage from the utility function, we treat consumer preference for low wattage as though it is entirely preference for low operating cost. If consumers also prefer low wattage for other reasons (e.g.: environmental), then we may be overestimating preference for low operating cost. Thus, our estimates of implicit discount rate may be biased downward.

## 4. Results and Discussion

### 4.1. Summary Statistics and Sample Characterization

Fifteen among the 183 subjects were removed from the analysis as explained in Section 3.1, and the remaining 168 subjects were used for this analysis.

Fig. 2 shows age and income distribution of the participant group in this study, juxtaposed with country-, city- (Pittsburgh), state-level (Pennsylvania) statistics retrieved from the 2010 U.S. Census (U.S. Census Bureau, 2010). Since the neighborhood where the study was performed has a large student population, the age group under 34 and the income group under \$10 k appear over-represented. Median tiers for income, education, and age were \$30–50 k per year, bachelor's degree, and age group 25–34. 56% of participants were male, 41% owned their houses, and 17% have children.

Ratings on seriousness of climate change were observed to be correlated with political view, but not with education or income: Liberal participants believed that climate change is a more serious issue than participants with different political views.

We also asked participants to rank the ten major technical factors that would affect their choice for light bulbs. When rankings of these factors were averaged numerically (a rough assessment), both with- and without-cost groups showed the same decreasing order: Brightness ≻ Price ≻ Lifetime ≻ Energy Cost ≻ Color ≻ Wattage ≻ Type ≻ Wattage Equivalent ≻ Time to Full Brightness ≻ Shape.

### 4.2. Main Results

Table 3 shows our main results. Models 1 and 2 show the results for a model that does not include consumer specific attributes, while Model 3 in the second column includes consumer attributes.

We also compute mean willingness to pay (WTP) derived from draws based on the parameter vector of the model and the variance covariance matrix from the estimation process incorporating the sampling variance (Hensher and Greene, 2003). We do not report all WTP results due to space limitations, but we discuss key findings, and additional information is available from the authors upon request.

WTP for a unit increase in variable *X* can be calculated taking ratios between $\beta^{X}$ and $\beta^{PRICE}$. However in our case, since many $\beta^{X}$ values and $\beta^{PRICE}$ are assumed to be random, we cannot simply divide one with the other. Instead, we use a Monte Carlo analysis, where we draw mean beta values from their joint distributions incorporating sampling variances and calculate the ratios for each draw. The mean of the ratios yields the population mean WTP of attribute *X*.[9]

### 4.3. Analysis

#### 4.3.1. How Do Dulb-Specific Factors Affect Consumer Choices?

From Model 2, we observed that, all else being equal, consumers generally prefer CFL technology and a relatively high level of brightness. Preferences for color and wattage are diverse: the standard deviations in the population are significant while the means are not, implying that some consumers prefer warmer color and lower wattage while others prefer the opposite. Preferences for low power ($p < 0.01$) and long life ($p < 0.1$) increase when operation cost information is provided.

Participants are willing to pay \$2.63 more for CFL bulbs than for incandescent bulbs on average, all else being equal; however, there was considerable variance, with some consumers willing to pay more for incandescent bulbs. Consumers are willing to pay \$0.52 more for every 1000 h of lifetime increase within the range tested in the experiment (1000 ~ 12,000 h), and that amount increased by \$0.14 when they were shown annual cost estimates. They are willing to pay \$0.46 more for every 10 W decrease within the range of 9 ~ 75 W when the annual cost information is shown.

#### 4.3.2. How Do Consumer-Specific Factors Affect Consumer Choices?

At the $p < 0.05$ level, liberals have a stronger preference for low wattage bulbs than non-liberals. At the $p < 0.1$ level, high income consumers have a stronger preference for long life than low income consumers, liberals have a stronger preference for CFLs than non-liberals, and people who correctly answer CFLs contain toxic materials and rate toxicity as "very dangerous" have a stronger preference for incandescent bulbs over CFLs than people who incorrectly answer or rate it as "not at all dangerous". Gromet et al. (2013) supports the finding that political ideology affects one's tendency to invest in energy efficient technology. Between Model 2 and 3 in Table 3, the significance of most coefficients for main technical features of bulbs did not change. The only change was that the mean coefficient of type variable becomes statistically insignificant suggesting that mean preference for this attribute is mainly induced by different levels of toxicity or political view, while the standard deviation remains significant meaning that the distribution itself is still significantly different from zero.

The relevance of various personal attitude variables in consumer decision making has been emphasized in multiple discrete choice studies, especially in the transportation sector (Ewing and Sarigöllü, 2000; Choo and Mokhtarian, 2004; Vredin Johansson et al., 2006; Domarchi et al., 2008). For example, Ewing and Sarigöllü (2000) investigated the effect of personal attitudes toward environment and technology on preferences for alternative fuel vehicles through a choice experiment. They found that while the attitudinal factors were significant, the increase in log-likelihood of the model due to the factors was not large. Teisl et al. (2008) suggested that consumers' perception or subjective concern for environmental problems together with eco-label information affected consumers' 'eco-behavior' such as purchasing greener vehicles. We observed that the findings from these studies applied similarly to lighting purchase decisions as well.

#### 4.3.3. What is the Right Level of Model Complexity for Policy Analysis and for Energy Models?

Table 3 presents the three models we test for this analysis. Among them, the MNL model (Model 1) is the simplest and the easiest to understand, but it has the highest AIC/BIC values compared to the other two models. A likelihood ratio test between Models 1 and 2 gives $\chi^2(8) = 457.1$ and $p < 0.001$, while a similar test between Models 2 and 3 gives $\chi^2(18) = 30.8$ and $p = 0.03$. Considering the relativity of statistical significance (depending on the significance level decision), the AIC/BIC results, and also the understandability of the model, we suggest that Model 2 addresses choice complexity and has the benefit of modeling consumer heterogeneity and avoiding the restrictive substitution patterns (i.e. IIA).

#### 4.3.4. How Does Disclosing Annual Operating Cost Information Impact Choices?

Models 2 and 3 show that having operating cost information is related to preferences for longer lifetime and lower wattage with no significant influence on choices for color, brightness, type, and price. According to the values in Model 2, and holding all other attributes constant, when the operating cost information was given a consumer was willing to pay \$0.14 more for a 1000-hour increase of lifetime and \$0.46 more for a 10 W decrease of power compared to the case where s/he did not see the information. A potential explanation for this is that when the annual operating cost information is given, consumers tend to pay more attention to the implications of lifetime and power on future savings.[10] The fact that lower power and longer lifetime affect consumer choices less when operating cost information is not shown is a potential reason why CFLs have underperformed in the market prior to introduction of packaging labels that incorporate operating cost estimates.

#### 4.3.5. What are the Implicit Discount Rates (IDR) that Consumers Use When Making Choices for Lighting Technologies?

We fit a nonlinear model as shown in Eq. (6) above including just the bulb attributes and the indicator of operating cost availability. We fit it separately for with- and without-cost groups and for three different income brackets (low/middle/high) to see the relationship between income and IDR. The discount rate estimates from this model are presented in Table 4. We found that average IDR is 100% for the with-cost group (i.e. with operation costs information) and 560% for the without-cost group (i.e. without operation costs information), and IDR decreases as income increases. Among the with-cost group, the IDR of the low income group was about five times larger than that of higher income consumers. However, in the without-cost group, the standard error of the low-income group was so large that we could not clearly say the low income group's IDR is higher than others. The high income group's IDR was significantly smaller than the mid-income group's value. Thus the higher up-front cost and delayed benefits of CFLs relative to incandescent bulbs is particularly pronounced for low to medium income groups and less of an issue for high-income groups.

In the experimental setting, the without-cost group was not provided with operating cost information, but with just the wattage of the bulb and the number of hours of operation. We assumed in Eq (6) that consumers' utility is represented by the annualized cost of ownership, such that the participants are inferring annualized operating cost from usage and power information during the choice process. The estimated IDRs in Table 4 suggest that consumers are pessimistic about (or pay little attention to) future economic savings delivered from the energy efficient

[9] I.e., given an estimated vector of beta from our model is B ($K \times 1$) and the estimated variance–covariance matrix is V ($K \times K$), we take N draws from MVN(B, V) (multivariate normal) distribution, which results in a matrix, D ($N \times K$). For each draw i ($i = 1, 2, \ldots, N$), we keep $b_i^X = \beta_i^X$ if βX is assumed normal or convert it to $b_i^X = exp(\beta_i^X + sd_i^{X2}/2)$ if βX is assumed log-normal. We calculate $E[b_i^X/exp(\beta_i^{PRICE} + sd_i^{PRICE2}/2)]$ over the N draws and use it as a mean WTP for attribute X.

[10] When operating cost information is presented, respondents also have more information to process. However, this information appears to affect only preferences for power and lifetime without significantly affecting other attributes.

**Table 4**
Estimates of implicit discount rates depending on income level and the availability of operation cost information.

| Implicit discount rates | Income level | | | Overall |
|---|---|---|---|---|
| | Low (below $30 k/year) | Middle ($30 k–75 k/year) | High (over $75 k/year) | |
| Operating cost shown | 182% (38%) | 57% (19%) | 36% (35%) | 100% (22%) |
| Operating cost not shown | 764% (315%) | 491% (49%) | 203% (73%) | 560% (70%) |

Note: standard errors in parentheses.

**Table 5**
Distribution of choices of light bulbs in the compensation choice task and predicted choices. The first two rows are for all 168 participants, the two rows in the middle are for the 83 participants who were not shown the operating cost information. The last two rows are for the 85 people who were given the cost information. Attribute values of these alternatives are shown in Fig. 2.

| | | CFL #1 | Incandescent #1 | CFL #2 | Total |
|---|---|---|---|---|---|
| All subjects | Observed # of choices | 59 (35.1%) | 30 (17.9%) | 79 (47.0%) | 168 |
| | Predicted % of choices | 31.1% | 24.2% | 44.7% | 100% |
| Without-cost group | Observed # | 32 (38.6%) | 20 (24.1%) | 31 (37.3%) | 83 |
| | Predicted % | 30.4% | 29.0% | 40.6% | 100% |
| With-cost group | Observed # | 27 (31.8%) | 10 (11.8%) | 48 (56.4%) | 85 |
| | Predicted % | 31.8% | 19.6% | 48.6% | 100% |

alternatives. It is possible that respondents who were not shown estimated cost information made different assumptions about energy prices or frequency of bulb use than the assumptions used to compute estimated annual operating cost information for the label, and it is not known which estimates are more accurate for individual consumers.

All of these estimated discount rates are on the high side in the ranges of discount rate values used in the NEMS (U.S. EIA, 2011). Savings from individual energy efficient light bulbs are normally smaller than savings from other energy efficient appliances, which may contribute to consumers choosing to use higher IDRs. This behavior was reported by Green et al. (1997). This finding suggests that lighting can face a higher barrier than other technologies with regard to the perception of operating cost information and potential reductions in energy bills. It also implies that while disclosing operating cost information as in the new FTC label will contribute significantly to further adoption of efficient light bulbs, it alone is not likely to be sufficient, and other policies with minimum efficiency standards (e.g. Section 321 of The Energy Independence and Security Act (EISA)) will be needed to achieve more savings.

*4.3.6. Model Validation Through Physical Choice Observations*

To examine the predictive accuracy of the estimated model, we first calculated population-wide choice probabilities of the three alternatives that were shown in the compensation task. These probabilities were computed using a variant of Model 2, which was estimated excluding the choices made by participants in the compensation task. Choice probabilities for each alternative were averaged over the distributions of the random coefficients to yield these probabilities.[11] In Table 5, we display the frequency of chosen alternatives in the compensation task and the population-wide choice probabilities predicted from the model respectively for all subjects, without-cost, and with-cost group.

Concurrent to this, we used our model to predict choice probabilities for the five physical samples presented in the second part of our experiment to test how our model predicts physical bulb choices. Physical choices and predicted choice probabilities are presented in Table 6.

In Table 7 we compare the results from estimates of choices using Model 2 with the choices made by participants in the compensation task, and with the choices made in the physical choice task. We further compare each of these with what the choices would be if one uses simply a random model that treats all choice alternatives as equally likely.

We use several metrics to compare across the choice probabilities estimated by our model, choices in the compensation task, choices in the task where participants were exposed to physical light bulbs, and the random model:

- *The log likelihood*: Log of the product of predicted probabilities for all observed choices. It indicates the goodness of the model fit.
- *The equivalent average likelihood* (*EAL*): The geometric mean of likelihood per choice made. It can be interpreted as the likelihood normalized to the size of the data. This metric was referred to as average hit rate by Feit et al. (2010), although it is more closely related to likelihood than hit rate.
- *The average hit rate* (*AHR*): The average probability that a draw from the model would match the choice observed for a randomly selected individual.
- *The average share prediction error*: The average value of the differences between predicted share and actual share.

Not too surprisingly, our model is better than a random model, offering a basic validity check. The improvement in EAL and AHR over the random model appears relatively small. However, these comparisons should be viewed with understanding that random utility choice models are not intended to predict every individual's choices separately, since individual choices themselves are stochastic. Rather, these models are intended to model aggregate behavior when integrated over the population, and the average share error of the model, an aggregate measure, is substantially better than random.

Our model predicts the choices for the compensation task with an average of 4.2% error, compared to 10.4% error for a random model. In the physical choice task, which involves unobserved technology attributes such as packaging, and brand, that were not present in the conjoint study, the model predicts share with an average of 5.7% error, compared to 9.6% error for a random model. These metrics suggest that attributes such as brand, packaging, shape, or size may play significant roles in choices, which we are not capturing in the model we estimated.

## 5. Conclusions and Policy Implications

We examine reasons for limited adoption of compact fluorescent bulbs using a choice-based conjoint experiment to quantify the effect of product and consumer attributes on consumer choice in conditions where annual operating cost estimates are disclosed vs. withheld. A caveat is that the subjects collected in this experiment over-represent young low income consumers.

Our results suggest that consumer choices are significantly affected by most bulb characteristics tested, including color, brightness, lifetime, power, type, and price. Perceived danger of toxicity in CFLs and political view are the consumer-specific factors that have significant influence

**Table 6**
Distribution of actual choices by subjects (in the order of popularity) and of predicted choice probabilities (in the order of size of probability) for physical sample choices.

| | CFL #2 | CFL #1 | CFL #3 | Incandescent #1 | Incandescent #2 | Total |
|---|---|---|---|---|---|---|
| Observed # of Choices | 74 (44.1%) | 33 (19.6%) | 32 (19.0%) | 23 (13.7%) | 6 (3.6%) | 168 |
| Predicted % of Choices | 30% | 27% | 19% | 15% | 9% | 100% |

[11] Numerical integration was used with 1000 draws from the random coefficients.

**Table 7**
Estimation statistics calculated for the three types of data with Model 1. The first column shows how well the estimated model fits with the observed data. The second column is about the predictive performance of the model. The last column indicates how well this model behaves in a realistic setting with additional unobserved attributes.

| | Estimation data | | Compensation task | | Physical choice | |
|---|---|---|---|---|---|---|
| | Model | Random | Model | Random | Model | Random |
| Log-likelihood | −1936 | −2399 | −173.7 | −184.6 | −243.1 | −270.4 |
| Equivalent average likelihood | 41.2% | 33.3% | 35.3% | 33.3% | 23.5% | 20.0% |
| Average hit rate | | | 36.3% | 33.3% | 24.5% | 20.0% |
| Avg. share prediction error | | | 4.2% | 10.4% | 5.7% | 9.6% |
| $N$ | $2184 = 168 * 13$ | | 168 | | 168 | |

on preferences for bulb attributes. Perceived severity of climate change or basic technical knowledge in lighting did not significantly affect preferences. This result suggests that educational efforts such as communicating the low risk of mercury in CFLs can be effective in driving CFL adoption, while linking CFL use and climate change mitigation is less to be helpful. However, our results suggest that these consumer-specific characteristics are not as significant in predicting consumer choices as bulb characteristics.

We find that providing operating cost information induces stronger preferences for bulbs with longer lifetime and lower energy consumption. Implicit discount rates (IDRs) decreased from over 560% to around 100% when respondents were provided annual operating cost estimates. The IDRs were observed to decrease as household income increases. This suggests that consumers weigh future savings more strongly when the information is given. The combination of these two findings put the new FTC labeling rule on a strong footing. The relationship between IDR and income suggests that higher-income consumers are more likely to adopt CFLs, and the high IDRs used by middle and lower income consumers presents a particularly large barrier to adoption.

Even when cost information is available, the estimated IDR for individual lamp choices of around 100% is still larger than most values used for other technology types in the NEMS model. Our findings can be meaningfully used to update such models. Future studies can examine why the discount rates are so high for lighting and whether alternative models such as hyperbolic discounting or models that account for satisficing behavior can explain consumer choices better than traditional economic discounting.

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