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Energy Efficient Lighting:

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Abstract

Lighting accounts for nearly 20% of overall U.S. electricity consumption, 14% of U.S. residential electricity consumption, and 6% of total U.S. carbon dioxide equivalent (CO_2e) emissions. A transition to alternative energy-efficient technologies could reduce this energy consumption considerably. We studied three questions related to energy efficiency lighting choices and consequences, which are:

- Question 1: How large is the system-wide effect of a residential lighting retrofit with more efficient lighting technologies?
- Question 2: Based on stated preference (SP) data, which factors influence consumer choices for general service light bulbs? What is the effect of the new lighting efficiency label mandated by the Federal Trade Commission?
- Question 3: What can we learn about market trends and consumer choices from consumer panel data (i.e. revealed preference (RP) data) for general service light bulbs between 2004 and 2009? How can we compare the findings from SP and RP data, and which findings are robust across the two?

In Chapter 2, we focus on the issue of lighting heat replacement effects. The issue is as follows: lighting efficiency goals have been emphasized in various U.S. energy efficiency policies. However, incandescent bulbs release up to 95% of input energy as heat, and it has been argued that replacing them with more efficient alternatives has a side effect in the overall building energy consumption: it increases the heating service that needs to be provided by the heating systems and decreases the cooling service that needs to be provided by the cooling systems. We

investigate the net energy consumption, CO_2e emissions, and saving in energy bills for single-family detached houses across the U.S. as one moves towards more efficient lighting systems. In some regions, these heating and cooling effects from more efficient lighting can undermine up to 40% of originally intended primary energy savings, erode anticipated carbon savings completely, and lead to 30% less household monetary savings than intended. However, this overall effect is at most one percent of total emissions or energy consumption by a house. The size of the effect depends on various regional factors such as climate, electricity fuel mix, differences in emission factors of main energy sources used for heating and cooling, and electricity prices. Other tested factors such as building orientation, insulation level, occupancy scenario, or day length do not significantly affect the results.

Then, in Chapter 3, we focus on factors that drive consumer choices for light bulbs. We collected stated preference data from a choice-based conjoint field experiment with 183 participants. We estimate discrete choice models from the data and find 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 is observed in conditions where estimated operating cost information was provided. Providing estimated annual cost information to consumers reduces 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 continue to use implicit discount rates of around 100%, which is larger than that estimated for other energy technologies.

Finally, we complemented the stated preference study with a revealed preference study. This is because stated preference data alone have limitations in explaining consumer choices, as purchases are affected by many other factors that are outside of the experimenter control. We investigate consumer preferences for lighting technology based on revealed preference data between 2004 and 2009. We assess the trends in lighting sales for different lighting technologies across the country, and by store type. We find that, across the period between 2004 and 2009, sales of all general service light bulbs are almost monotonically decreasing, while CFL sales peaked in 2007. Thanks to increasing adoption of CFLs during the period, newly purchased light bulbs contributed to lowering carbon emissions and electricity consumption, while not sacrificing total produced lumens as much.

We study consumer preferences for real light bulbs by estimating choice models, from which we estimate willingness-to-pay (WTP) for light bulb attributes (watt and type) and implicit discount rates (IDR) consumers adopt for their purchases. We find that the campaign for efficient bulbs in Wal-Mart in 2007 is potentially related to the peak in CFL adoption in 2007 in addition to the effects of the EISA or other factors/programs around the same period. Consumers are willing to pay, $1.84 more for a change from an incandescent bulb to a CFL and -$0.06 for 10W increase, the values which also include willingness-to-pays for corresponding changes in unobserved variables such as life and color. IDRs for four representative states range between around 230% and 330%, which is in a similar range we estimate from the choice experiment.

Overall, even with energy efficiency labels, nationwide promotion of CFLs by retailers, or better availability of CFLs in the transforming residential lighting market, we see the barriers to energy efficient residential lighting are still persistent, which are reflected in high implicit discount rates observed from the models. While we can expect the EISA to be effective in lowering the barriers through regulation, it alone will not close energy efficiency gap in the residential lighting sector.

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For the last, I cannot thank more to my lovely wife, Heejung Kang, and my parents for always standing by me.

Acronyms and Abbreviations

AEO: Annual Energy Outlook

AHR: Average Hit Rate

AIC: Akaike Information Criterion

BIC: Bayesian Information Criterion

BTU: British Thermal Unit

CFL: Compact Fluorescent Lamps

CO_2e: Carbon Dioxide Equivalent

DEFRA: Department of Environment, Food, and Rural Affairs

EAL: Equivalent Average Likelihood

EIA: Energy Information Agency

eGRID: Emissions & Generation Resource Integrated Database

EISA: Energy Independence and Security Act

FTC: Federal Trade Commission

HOU: Hour(s) of Use

HRE: Heat Replacement Effect

IDR: Implicit Discount Rate

IECC: International Energy Conservation Code

IIA: Independence of Irrelevant Alternatives

IPCC: Intergovernmental Panel on Climate Change

LED: Light Emitting Diode

LPD: Lighting Power Density

MCMC: Markov Chain Monte Carlo

MNL: Multinomial Logit

NEMS: National Energy Modeling Systems

NERC: North American Electric Reliability Corporation

PNNL: Pacific Northwest National Laboratory

RECS: Residential Energy Consumption Survey

RP: Revealed Preference

SP: Stated Preference

UPC: Universal Product Code

WTP: Willingness-to-pay

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1. Introduction and motivation

1.1. Energy efficiency policies in the U.S.

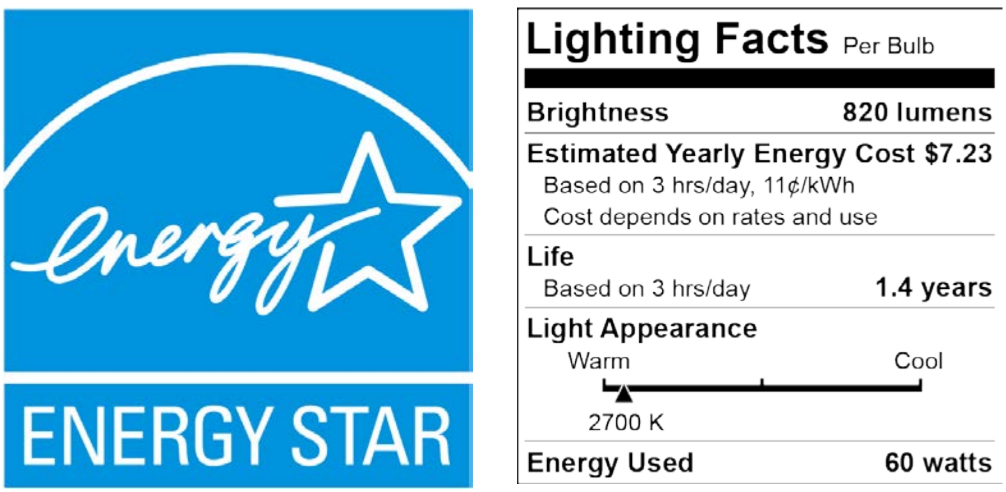
Energy efficiency was brought to our attention as a major energy policy target in the wake of the 1970s oil crisis. Energy efficiency policies span a very wide range from developing appliance standards to sponsoring research and development for efficient technologies (Doris et al., 2009) Among them, policy measures which directly influence individual residential consumers are mainly for two sectors: buildings and transportation. There are common approaches across the two sectors which intend to promote adoption of more efficient technologies. The first approach is to set efficiency standards on buildings, appliances or vehicles. Examples are Corporate Average Fuel Economy (CAFE) or Title III of Energy Independence and Security Act (EISA) of 2007. Specifically for the building sector, building codes are another type of standards that contributes to fostering building energy efficiency. Such codes help control building attributes, such as insulation, lighting, and heating, ventilation, and air-conditioning (HVAC), all of which determine energy consumption from buildings. Another approach is to adopt labeling programs which can inform consumers of better information about energy use of products. Two main types of labels are endorsement and comparative labels (Doris et al., 2009). A good example of an endorsement label is Energy Star, and an example of a comparative type is a sticker label on windows of new cars showing fuel efficiency information. Yet another approach is to provide financial incentives for more efficient products, such as tax credits, loans, subsidies, or rebates. Sometimes, governments can also provide non-financial incentives such as exclusive access to fast lanes to efficient vehicles. This dissertation, which focuses on a specific energy service—

residential lighting—encompasses policy issues of energy labeling on light bulb packages and building energy codes in the U.S.

1.2. Policies related to lighting in the United States

In order to increase energy efficiency specifically for the lighting sector, the U.S. government has been taking various approaches. Section 321 of Title III in the Energy Independence and Security Act (EISA) of 2007 is a key element among them. EISA raises minimum efficiency standards of general service light bulbs. It defines general service lamps as having a medium screw-base (i.e. E19 socket) with brightness range between 310 and 2600 lumens and voltage range within 110 and 130 volts. Since incandescent lamps have lower efficacy than other types, the act is likely to lead, in practice, toward a phase-out of incandescent lamps, unless new technology improvements make it such that they can meet the minimum requirements. The act does not apply to other special purpose lamps (H.R. 6-110th Congress, 2007).

Another type of intervention is to help consumers better understand what lighting products they are purchasing through the use of labels or certification marks. Light bulbs or fixtures that can satisfy the specifications established by the U.S. Environmental Protection Agency (EPA) are qualified for Energy Star label. This label itself is a pictorial label, which does not show any technical details, as shown in Figure 1.1a. For light bulbs, the EPA specifications demand minimum levels of efficacy, color rendering index, and lumen maintenance. Correlated color temperature (CCT) has to be one of the designated levels. These requirements are different for CFLs and LEDs. Apart from this Energy Star label, the Federal Trade Commission (FTC) mandated, as of January 1, 2012, that most general purpose lamps with medium screw bases have to include a new descriptive label on front and back sides of packages in order to help consumer choices (FTC, 2013). This label has to include information about brightness, estimated operation cost, wattage, rated lifetime, light color, and whether the bulb contains mercury. A picture of this label is shown Figure 1.1b for illustration.



(a) (b)

Figure 1.1 Two energy efficiency labels relevant to lighting. a) Energy Star; b) the FTC “Lighting Facts” label

Building energy codes are also a crucial mechanism affecting efficiency of lighting systems used in buildings. There are two major building codes standards used in the United States: the International Energy Conservation Code (IECC) and ASHRAE standard (American Society of Heating, Refrigerating and Air-Conditioning Engineers). ASHRAE 90.1 is a building energy standard for buildings except low-rise residential buildings, which sets minimum lighting power density standards[1] for various types of commercial building areas (e.g. hotels, libraries, offices, etc.). The IECC is mainly adopted for residential building code, while combinations of the two are widely used for commercial code by many states. These standards are updated and released regularly, and states have been adopting different versions. The most widely adopted versions are 2009 IECC for residential buildings and ASHRAE 90.1 - 20007/2009 IECC for commercial buildings (U.S. DOE, 2013). The 2012 version of the IECC requires at least 75% of lamps installed in a residential building to be high-efficacy. High-efficacy is defined as having minimum efficacy of 40 lm/W for less than 15W lamps, 50 lm/W for lamps between 16 and 40W, and 60 lm/W for lamps over 40W. As of March 2014, the IECC is adopted by 42 states for their residential code, and ASHRAE 90.1 is adopted by 43 states for their commercial code (U.S. DOE, 2013).

1.3. Structure of this dissertation

The first chapter in the main analysis (Chapter 2) investigates the system-wide effect of switching to efficient lighting system. It is a work based on a series of building energy simulations, which aims to understand interactions among different energy end-uses in residential buildings. Chapter 3 assesses consumer preferences for residential lighting based on stated preference data from a choice-based conjoint experiment. Chapter 4 adopts consumer panel data and observes the trends of light bulb purchases between 2004 and 2009. Chapter 5 analyzes the revealed preference data and models consumer choices similarly to the models from Chapter 3. By comparing the findings from the two different datasets, we try to understand more

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[1] Lighting power density is a measure of lighting power consumption in a building space. It represents lighting energy consumption per unit area and has a unit of watt per square feet (W/ft^2).

about consumers' preferences and behaviors around energy efficiency and lighting. The last chapter, Chapter 6, will summarize the key findings from this work, and provides more thoughts on the policy implications.

2. Understanding heat replacement effects across the U.S.

2.1. Introduction

In order to reduce emissions, improve energy security and avoid building as much additional electricity generation infrastructure, the U.S. has been fostering improvements in energy efficiency. In particular, energy efficient lighting has been promoted in many energy efficiency programs by utilities. Switching from low efficiency lighting technologies, such as incandescent light bulbs, to compact fluorescent lamps (CFL) or light emitting diodes (LED) can provide the same level of illumination while consuming less power and thus reducing lighting electricity bills to consumers. The potential for reductions in energy consumption, in greenhouse gas emissions, and in criteria air pollutant emissions is large, as lighting accounts for 19 percent of U.S. electricity consumption (Navigant Consulting, 2012) and 6 percent of CO_2 equivalent emissions (U.S. EPA, 2013). We focus on the residential sector, where lighting accounts for 14 percent of total residential electricity consumption and 9 percent of total residential primary energy consumption in 2011(U.S. EIA, 2013).

In many assessments of energy and cost savings from lighting retrofits, modelers use engineering analyses comparing lighting systems before and after an energy efficiency measure is implemented, assuming all other energy demands are held constant. However, the substitution of incandescent light bulbs (where about 95 percent of the electricity is released as heat) with more efficient alternatives, such as compact fluorescent lamps or light emitting diodes, will lead to additional heating and reduced cooling energy consumption, which is generally called a "*heat replacement effect*" or HRE (Young, 2003). This HRE can be interpreted as a component of the *rebound effects*, i.e., the percent of energy or carbon dioxide emissions savings that were not achieved due to behavioral or technical reasons. In this work, we assess the magnitude of HRE across the United States, changes in household energy bills, and associated indirect carbon emissions for single-family detached buildings across 105 cities in the contiguous U.S when incandescent light are switched to more efficient alternatives.

HRE has been studied through experiments using physical test chambers equipped with instruments measuring actual heat transfer (Mitalas, 1974; Treado and Bean, 1992; Chantrasrisalai and Fisher, 2007). These experiments, mainly designed for the benefit of building engineers, can estimate the lighting heat gain parameters for the experimental setup as a function of detailed parameters such as luminaire type, room air temperature, or airflow rate, types of information which are only available at a specific building level.

HRE has recently become a more prominent subject of policy discussion: in the U.K, the Department of Environment, Food, and Rural Affairs (DEFRA) assessed the impact of HRE on energy consumption, consumer energy bills, and carbon savings in the U.K. residential sector (Market Transformation Programme, 2010). DEFRA found that 24 to 26 percent of total anticipated light energy savings would be lost due to HRE. In the United States, most of the analysis and discussion has focused on commercial buildings (Sezgen and Huang, 1994; Sezgen and Koomey, 2000). These studies found no significant net gains or losses at a national level in primary energy (or source energy) use or energy expenditures for heating, ventilation, and air conditioning (HVAC). Hopkins et al. (2011) provided a simple order-of-magnitude analysis of HRE of a residential lighting retrofit as a part of their report on a simulation tool developed to estimate nationwide residential energy use based on a nationally representative set of single-family residential buildings. Hopkins *et al.* report that for each unit of site energy savings due to lighting retrofits, there will be an additional 7 percent site energy savings from reduced use of AC, while 40 percent will be lost to satisfy additional heating demand on site (i.e. resulting in only 0.67 (=1+0.07-0.40) net units of energy being saved). Overall, the authors report that the net primary energy savings resulting from each unit of site energy saving is 0.95.

2.2. Data and methods

Data

We use EnergyPlus 7.2 version for our analysis. EnergyPlus is a comprehensive building energy simulation program developed by U.S. DOE. It runs building energy simulations based on a formatted description of a building. Users create the description file by specifying fields predefined in EnergyPlus, which correspond to detailed components of a building (e.g. building dimensions, structure of heating/cooling systems, wall/window characteristics). EnergyPlus outputs site/source energy consumption categorized by end use and fuel type.

We adopt building prototypes created by Pacific Northwest National Laboratory (PNNL) as input.[2] PNNL's prototypes represent buildings compliant with the International Energy Conservation Code (IECC) of 2006, 2009, or 2012 – thus representing recently constructed residential buildings. New single-family houses built since 2006 in the U.S., which are covered by the PNNL prototypes, represent about 8 percent of residential building stock.[3] The IECC is

[2] Pacific Northwest National Laboratory (2012) Residential Prototype Building Models. ed U.S. Department of Energy. http://www.energycodes.gov/development/residential/iecc_models

[3] U.S. Census Bureau (2011) Building Permits Survey - New Privately Owned Housing Units Completed (United States Census Bureau). http://www.census.gov/construction/nrc/pdf/compann.pdf

developed by the International Code Council and adopted by most state or local governments as a basis for their building energy efficiency requirements. We use the prototypes complying with IECC 2009 since as of 2012 it is the baseline code most widely adopted by states for their building energy codes, having been adopted by 30 states.[4]

The PNNL prototypes characterize single-family detached houses and multi-family low-rise apartment buildings in 109 U.S. cities while assuming well-mixed interior for the simulation. We focus on single-family detached houses, as they account for the majority (about 75 percent) of total residential electricity consumption in the United States (U.S. EIA, 2009). We simulate the prototypes corresponding to 105 cities in the contiguous U.S. The PNNL prototypes differ only in their U-factors and SHGC (Solar Heat Gain Coefficient) values for windows and R-values for exterior materials, which vary by climate zone to be in compliance with the IECC requirements. An R-value is a measure of thermal resistance and represents a reciprocal of how much heat energy is transferred per unit area of a material when a unit temperature difference is applied across it, measured in $m^2 \cdot °C/W$ or $ft^2 \cdot °F \cdot h/Btu$. As such, a higher R-value means better insulation capability. The U-factor is the inverse of R-value and measures thermal transmittance.

The PNNL single-family house prototypes have two stories, an attic, two doors on the south and north sides, and a window on all four sides of each floor. Four foundation types are modeled (slab, crawlspace, unheated and heated basement), as well as four heating systems (gas/oil furnaces, electric resistance, and heat pump), resulting in sixteen combinations. The floor area is $224m^2$ ($=2411ft^2$). The window-to-wall ratio is 15 percent. Thermostat settings are assumed to be 72˚F for heating and 75˚F for cooling.

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[4] U.S. Department of Energy (2013) Status of State Energy Code Adoption. ed Energy Efficiency and Renewable Energy. https://www.energycodes.gov/status-state-energy-code-adoption

Houses with slab foundation and gas heating are used as a base-case in our analysis, since they are the largest group among the residential building stock. The 2009 Residential Energy Consumption Survey (RECS) microdata[5]—designed to be nationally representative—shows that among all the 7,803 single-family house observations in RECS 2009, those with slab foundation and gas heating systems take 14 percent. In the sensitivity analysis we will assess the impact of having different types of heating system or foundation. In Table 2.1in the appendix, we show the proportion of buildings with each type of heating equipment and foundation among the 7,803 single-family houses.

Weather data for the typical meteorological year for each of the 105 cities was retrieved from the U.S. DOE's Energy Efficiency and Renewable Energy (EERE) website.[6] We used the TMY3 dataset, which is derived from the period 1991-2005 and contains hourly values of solar radiation and other meteorological data. Average electricity prices for each state and natural gas price for residential consumers for year 2010 were collected from U.S. Energy Information Agency (EIA) electricity data website.[7,8] Average carbon emission factors are from U.S. Environmental Protection Agency (EPA)'s eGRID database, and primary energy conversion factors for each state were adopted from Deru and Torcellini (2007). Building occupancy is characterized in EnergyPlus by defining two inputs: household size and daily occupancy profile. We assume a

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[5] U.S. Energy Information Administration (2009) Residential Energy Consumption Survey. (Energy Information Administration). http://www.eia.gov/consumption/residential/

[6] Energy Efficiency and Renewable Energy (2012) Weather Data. http://apps1.eere.energy.gov/buildings/energyplus/cfm/weather_data3.cfm/region=4_north_and_central_america_wmo_region_4/country=1_usa/cname=USA

[7] U.S. Energy Information Administration (2011) Average retail price for bundled and unbundled consumers by sector. in *Electric Sales, Revenue, and Average Price.* http://www.eia.gov/electricity/sales_revenue_price/

[8] U.S. Energy Information Administration (2010) Natural Gas Prices - Residential Price. http://www.eia.gov/dnav/ng/ng_pri_sum_a_EPG0_PRS_DMcf_a.htm

household size of three people, and the default occupancy schedule is as in PNNL prototypes (see Figure 2.9 for more detail).

Simulation scenarios

We assume a baseline lighting demand scenario and an efficiency scenario. The baseline scenario represents average lighting energy consumption of a single-family detached house meeting IECC 2009. We calibrate this profile by using lighting energy consumption from the 2010 U.S. lighting market characterization produced by Navigant Consulting for the DOE (Navigant Consulting, 2012). Based on that report, installed bulbs in single-family residential buildings are 68 percent incandescent, 24 percent CFL, and 8 percent linear fluorescent lamp. This differs from the lighting requirement of IECC 2009, which requires at least 50 percent of the lamps to be high-efficacy. This share distribution in 2010 is converted to average interior illuminance of 276 lux and lighting power density (LPD) of 12.2 W/m2. The diurnal lighting usage schedule is adopted from the Building America Simulation Protocol (Hendron and Engebrecht, 2010) and scaled to match the average daily hours of use from the Navigant report of 1.45 hour per lamp (see Figure 2.10 for more detail on lighting profiles).

The efficiency scenario complies with the lighting requirement of IECC 2012, which requires residential buildings to have at least 75 percent of the lamps being high-efficacy (Lucas et al., 2012). IECC 2012 was selected because this code is growingly being adopted by states. Building on the baseline assumption on shares above, we assume 25 percent incandescent, 67 percent CFL, and 8 percent linear fluorescent lamps, which corresponds to average LPDs of 7.4 W/m2. Indoor illuminance level and hours of use are kept unchanged across scenarios, i.e., we do not account for rebound effects resulting from using efficient lamps for more hours (see Azevedo et al. (2012) for a taxonomy on rebound effects).

2.3. Results

We compare a *baseline* scenario and an *efficiency* scenario for single-family detached houses with slab foundation and gas furnace in 105 cities around the contiguous U.S.

We compute the size of HRE as follows:

$$HRE\ [\%] = \frac{(C_{baseline} - C_{noHRE}) - (C_{baseline} - C_{HRE})}{C_{baseline} - C_{noHRE}} \times 100\% = \frac{C_{HRE} - C_{noHRE}}{C_{baseline} - C_{noHRE}} \times 100\%, \qquad (2.1)$$

where C can either represent primary energy consumptions, CO_2e emissions, or energy bills. Thus, an HRE of 20 percent in primary energy savings, for example, means that out of 100 units of anticipated primary energy savings, only 80 units of savings are actually achieved once HRE is taken into account. In this way, HRE can be interpreted as a technical rebound effect. A detailed explanation of this term is provided in Section A2.1 of the appendix.

Figure 2.1 shows total annual average primary energy (i.e. source energy) consumption (Figure 2.1a), CO_2e emissions (Figure 2.1b), and household energy expenditures (Figure 2.1c) at the baseline scenario for single-family detached houses with slab foundation and gas furnace in each of the 105 cities. CO2e emissions (metric tonCO2e per year) account for both direct and indirect emissions of CO_2, CH_4, and N_2O for natural gas and electricity consumption for all end-uses. For the global warming potential of the gases, we used values released by IPCC (Intergovernmental Panel on Climate Change) AR5 for 100 years of lifetime. Total energy expenditure is the total annual energy bills for both natural gas and electricity for all end-uses using state level residential prices for electricity and natural gas. We use 2010 average state level retail residential electricity prices as reported by the Energy Information Administration, and an assumed natural gas retail price of $11.4 per thousand cubic feet. All prices and costs are in 2010 dollar. In the sensitivity analysis we assess the importance of these assumptions on our results.

In the baseline scenario, across the 105 cities, a detached house can consume between 10 and 25 GJ of primary energy annually for lighting, while they all consume identical site energy (5.2GJ = 1.5MWh) for lighting. This variation in primary energy consumption derives from differences in the electricity generation mix in each region, and associated differences in efficiency. Total annual primary energy use (including water heating and appliances) range from 150 to 330 GJ per household (Figure 2.1a). Total annual CO_2e emissions from electricity and natural gas consumption per household range from 5 to 20 ton CO_2e (Figure 2.1b). Finally, total annual spending on energy (gas and electricity) ranges from $1,700 to $3,600 (Figure 2.1c).

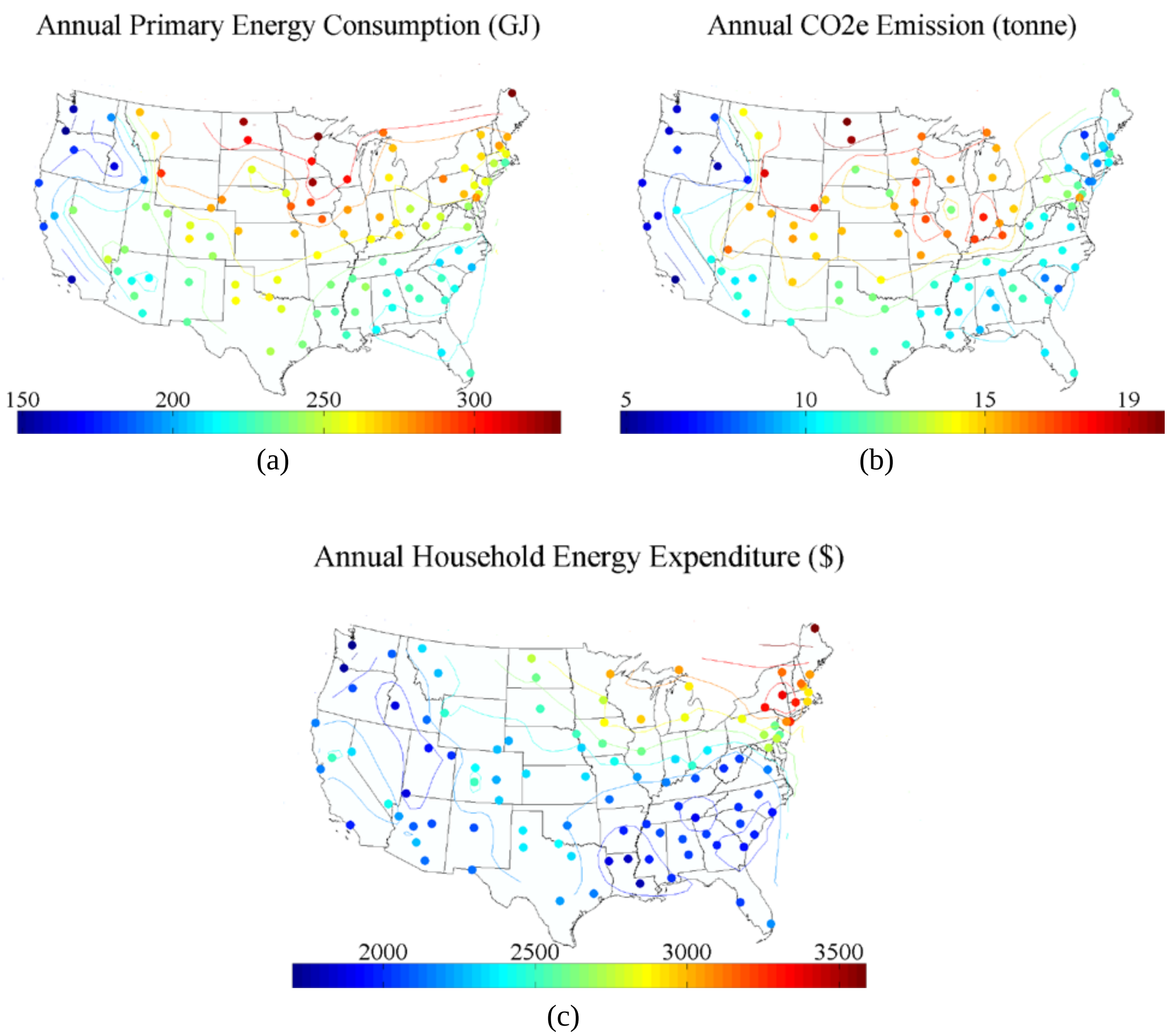


Figure 2.1 Total baseline a) primary energy consumption, b) CO_2e emissions, and c) household energy expenditures (natural gas and electricity) for single-family detached houses with slab foundation and gas furnace in each of the 105 cities.

In the appendix, section A2.2, we show percent savings, without HRE accounted for, of primary energy consumption, CO2e emissions, and household energy expenditures for single-family detached houses with slab foundation and gas furnace in each of the 105 cities. A first key conclusion is derived from such assessment: lighting interventions that are aiming at compliance with IECC 2012 can lead at most to a 4 percent reduction at a building level in total household primary energy consumption, total CO2e emissions, or energy expenditures. The magnitude is reasonable considering that lighting consumes at most 9 percent of total residential primary energy use. It is noteworthy that even when HRE for lighting is large, we can anticipate that the effects in overall household energy consumption, emissions or expenditures will be small.

Figure 2.2 highlights the changes in the results when we account for HRE. Figure 2.2a, 2.2c, and 2.2e show total savings of annual primary energy, CO2e emissions and energy expenditures between the baseline and efficiency scenario once HRE is taken into account.

Figure 2.2b, 2.2d, and 2.2f show the size of HRE in primary energy savings, CO2e emissions savings and annual cost savings when HRE is accounted for. As defined in Equation (2.1), negative numbers in these figures mean that there are more savings than anticipated, while positive values mean that some of the savings are eroded due to HRE.

Primary energy savings. HRE doesn't always lead to reduction in energy savings. In the Southern U.S., for example, switching to more efficient lighting systems lowers the need for AC during the summer months. This reduction exceeds the increase in heating demand during the relatively short winter season, leading to about 22 percent more energy savings than what is anticipated when HRE is not taken into account (Figure 2.2b).

Conversely, most of northern cities experience final energy savings smaller than what would be predicted if HRE is not taken into account. In those cities, the increase in energy consumption for heating due to HRE outweighs the relatively small decrease in demand for cooling.

Furthermore, in some states such as Washington, Idaho, and Oregon, their large proportion of power provided by hydroelectric generators leads to low primary energy conversion factors, making their final primary energy savings lower than other states (Deru and Torcellini, 2007). The size of HRE in primary energy savings in these states can be as high as 40 percent (dark blue dots in Figure 2.2b), meaning that among 100 units of primary energy savings expected from a more efficient lighting system, only 60 will be achieved.

In contrast, houses in Florida can achieve up to 20 percent more primary energy savings than expected because the cooling energy service can be lowered (dark red dot in Figure 2.2b). When the absolute HRE size is compared with total baseline primary energy consumption, the largest penalty on the intended energy savings is observed in Seattle, WA: under our baseline assumptions, total energy use was 155GJ and the efficient lighting system, without accounting for HRE, is expected to save 3.6GJ; the size of rebound due to HRE amounts to 1.4GJ, or 0.9 percent of total baseline energy consumption.

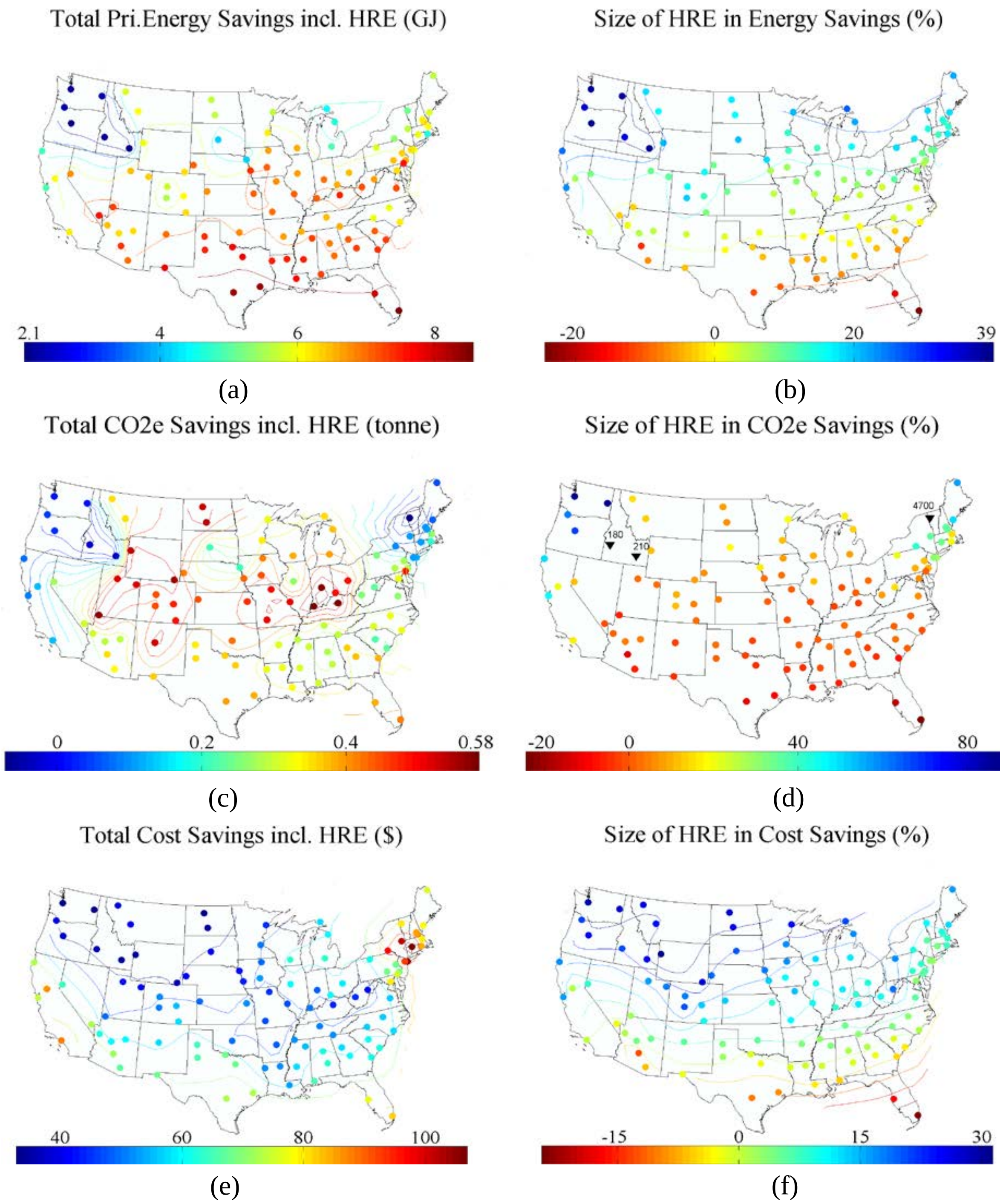


Figure 2.2 Total savings resulting from the retrofit with HRE accounted for (left column), and corresponding size of HRE (percent of total savings that are not achieved because of HRE) (right). a) Primary energy savings when HRE is accounted for, in GJ per year; b) size of HRE in terms of primary energy savings; c) CO_2e emissions saved annually when HRE is accounted for, in kg of CO_2e; d) size of HRE in term of CO_2e emissions savings; e) reduction in energy bills (electricity and natural gas) achieved annually after HRE is accounted for, in 2010 USD per year; f) size of HRE in energy cost savings. Contour lines for d) are not presented since the values of the three cities marked with "▼" are too much out of range and would lead to poorly scaled contour lines.

CO_2e emissions savings. CO2 equivalent emission savings are mostly determined by emission factors from the electric grid. We adopted state-level average carbon emission factors from U.S.EPA's eGRID database.[9] In two states with substantially low emission factors for electricity, Idaho (0.13 lb/kWh) and Vermont (0.006 lb/kWh), a lighting retrofit results in larger emissions of CO_2e than the baseline emissions, thus having a HRE size higher than 100 percent. Since the sizes of HRE in the two states significantly out-lie the rest of the cities, we mark them in Figure 2.2d with "▼" and corresponding percentage values next to the marks. Burlington, VT exhibits a tremendous rebound in emission savings: the city increases its CO_2e emissions by forty seven times compared with what it intend to save as it switches to more efficient lights. This is because any forms of electricity savings in this state yields almost no CO_2e reduction due to its near-zero emission factor for the electricity grid, while the emission from increased natural gas use for space heating easily exceeds the small reduction. Two other northwestern states (Washington and Oregon) and Maine, which have very low grid emission factors for electricity, have hardly any emission savings from improving lighting efficiency. On the other hand, in Lexington, KY and Evansville, IN (dark red dots in Figure 2.2c), we observe the largest emission savings out of the 105 cities considered, as these states have one of the largest grid emission factors for electricity in the country. The percentage of total baseline CO_2e emissions that are negatively affected by HRE is largest in Arcata, CA, which is 1.3 percent. The city has the sixth lowest total emission and the lowest cooling demand among the 105 cities at the baseline.

Household energy expenditures. Buildings located in southern states save more when HRE is accounted for than when they are not (i.e. negative HRE size), but the situation is opposite in

[9] U.S. Environmental Protection Agency (2012) eGRID2012 Version 1.0. http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html

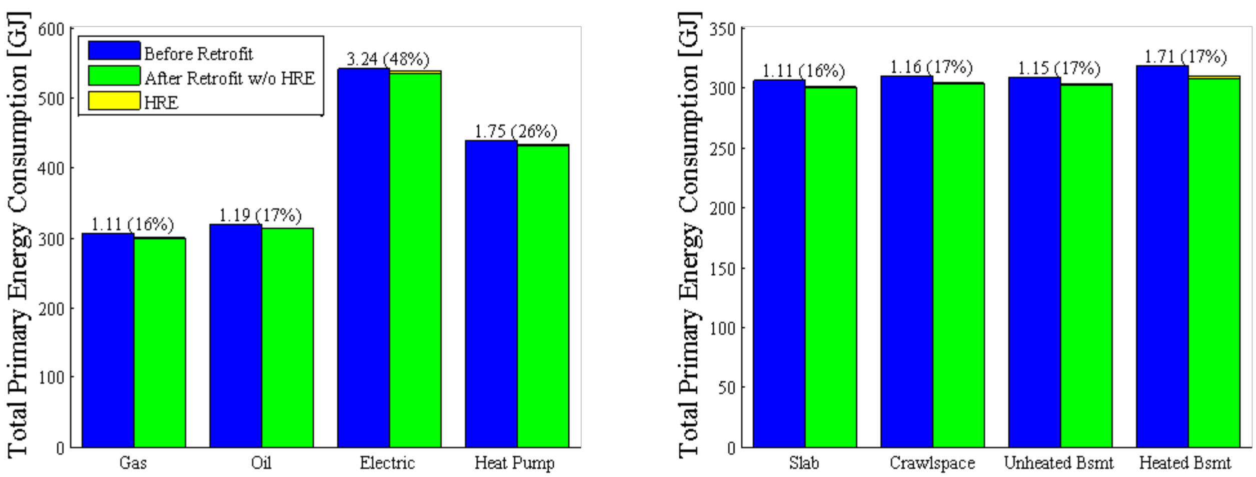
most other states. For example, a household in Jackson Hole, Wyoming would expect to save $50 a year from the efficient lighting system but HRE reduces the savings by $16 (31 percent less, shown as a dark blue dot in Figure 2.2f), while another household in Florida saves $83 a year, which is 24 percent more than what is anticipated without considering HRE (=$66). States with higher electricity price (such as California and the New England region) benefit more from lighting retrofits and see annual energy expenditure savings of up to $110 per year.

2.4. Sensitivity analysis

Throughout the analysis, we took the strategy to pursue several modeling assumptions. Indeed, there is a large uncertainty concerning what carbon emissions factors one should use in these sorts of assessments, the types of efficiency retrofits a household could do, the influence of the house heating and cooling equipment type, type of housing foundations, changes in electricity and natural gas retail prices over time, change in occupancy, etc. To understand the impacts of the assumptions used in the building models on heat replacement effects, a series of sensitivity analyses are conducted. The assumptions tested are: 1) heating equipment and building foundation type, 2) carbon emissions factors for electricity, 3) energy prices, 4) building orientation, 5) efficiency value of heating/cooling equipment, 6) wall insulation level (R-values), 7) occupancy schedule, and 8) lighting use schedule.

Sensitivity of results to type of heating equipment and building foundation

The findings presented so far are limited to houses with gas furnaces and concrete slab foundations. In Figure 2.3, we compare primary energy consumption for several types of heating systems and building foundations for Bismarck, North Dakota. This city has one of the largest temperature ranges over the course of a year amongst the 105 U.S. cities studied, and so has both substantial heating and cooling demands. Not surprisingly, heating systems powered by electricity consume much more primary energy. HRE size for electrically heated houses is larger than the alternatives (Figure 2.3a). Foundation types do not affect the total energy consumption in a notable manner (Figure 2.3b). Depending on the heating equipment type, HRE size in Bismarck, North Dakota, ranges from 16 percent (for natural gas powered heating) to 48 percent (for electricity based heating).



(a) (b)

Figure 2.3 Effect of different main heating fuels and types of building foundations on total primary energy use and HRE. a) Effect of heating fuel types for a building with slab foundation in Bismarck, ND; b) Effect of building foundation types for a building with gas heating in Bismarck, ND. The numbers on the bars show the size of HRE both in absolute terms (in GJ) and in relative terms (percentage out of intended savings).

Sensitivity of results to carbon emission factors

Grid emission factors for electricity in each state will naturally affect total CO_2e emission from a household and consequent size of HRE. Moreover, for each emission factor value, the size of

HRE will also vary depending on which fuel (mainly electricity or natural gas) a building primarily uses for heating. For Bismarck, ND, we assessed the sensitivity of HRE size in CO_2e emissions savings with respect to emission factors, assuming overall values of 0.6, 1.2, and 2.2 lb/kWh, and assuming scenarios of either electric or natural gas heating. The size of HRE is sensitive to grid emission factors only in gas-heated buildings. For buildings with electric heating, both increases and decreases in household energy demand resulting from a lighting retrofit are from electricity. Therefore, the resulting size of CO_2e emissions rebound due to HRE are simply proportional to total intended emissions savings. On the other hand, when a building is heated mainly by natural gas, and the emission factor for electricity is low, additional emissions from heating energy use become relatively large compared to a decrease due to electricity savings. This effect is shown in Figure 2.4, where the size of HRE increases as emission factors become smaller (7 percent →16 percent →43 percent).

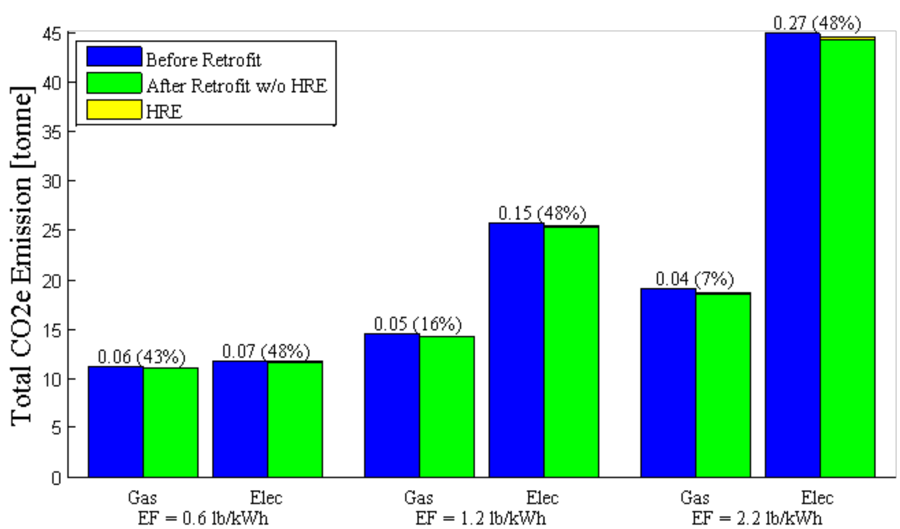
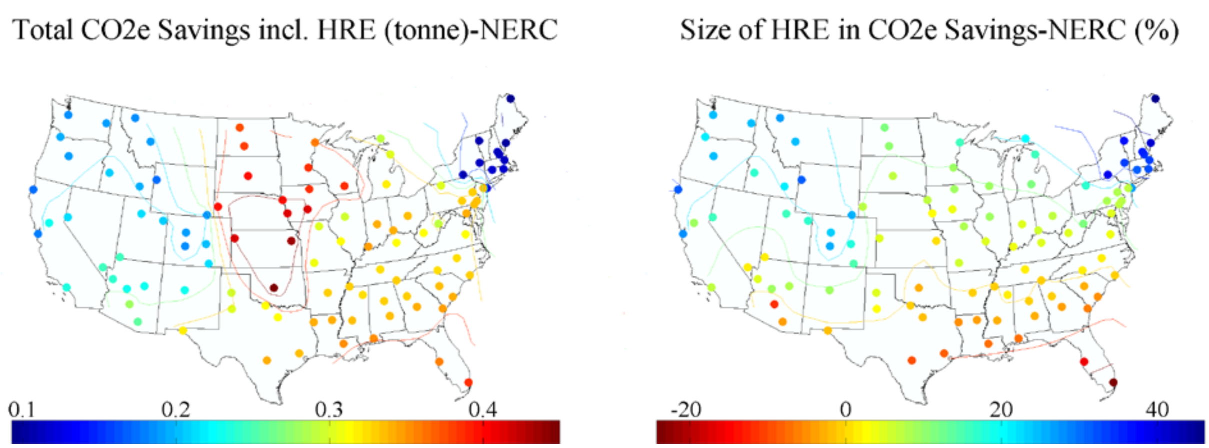


Figure 2.4 Effect of changes in carbon dioxide emission factor on CO_2e emission savings for houses with either gas or electric heating in Bismarck, ND. The numbers on the bars show the size of HRE both in absolute terms (in tonnes) and in relative terms (percentage out of intended savings); EF = emission factor.

The main analysis in the result section makes use of state-level electricity emission factors based on eGRID 2012 data. We test now how the analysis changes depending on which set of emission factors we adopt. Instead of state-level data, here we adopt NERC (North American Electric Reliability Corporation) region-level emission factors from the same database. Since each NERC region includes multiple states, using the NERC values acts as taking spatial averages across states in each region. Because of this averaging effect, extreme values are removed, and Figure 2.5b a now has a lot narrower range of values than Figure 2.2c. In Figure 2.5b, we do not see cities with the size of HRE larger than 100 percent (which was the case in Figure 2.2d for Vermont and Idaho). Caribou, ME becomes a city with the largest size of HRE (46 percent). This comparison suggests that relying on data at a different regional scale may lead policy makers to aim at lower priority targets. For example, our analysis based on state emission factors indicates that either Kentucky or Indiana is the state with the largest carbon savings while the result in Figure 2.5 shows it will instead be Oklahoma.

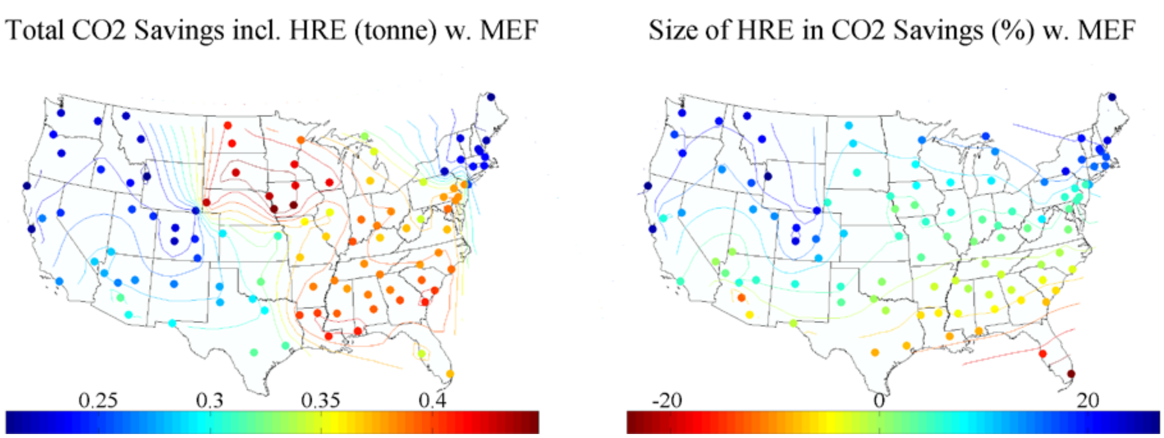


(a) (b)

Figure 2.5 Annual CO_2e emission savings based on NERC region-level emission factors. These maps are analogous to Figure 2.2c and 2.2d, which were based on state-level emission factors.

We also show how our results change at each location if one uses marginal emission factors (MEF) instead of average emission factors (Figure 2.6). We adopt time-of-day average annual MEFs for each NERC region from Siler-Evans et al. (2012) As mentioned in that work, the

Southwest Power Pool (SPP) region (overlapping mainly with Oklahoma and Kansas) has an average emission factor (760 kg/MWh) significantly higher than MEF (around 560 kg/MWh) because of the large amount of coal used for its base load. Other than SPP, most regions have MEFs similar to or higher than average emission factors, resulting in larger emission savings from a lighting retrofit. For this reason, in Figure 2.6 we observe larger carbon savings and smaller sizes of HRE than when average emission factors are used. Only the SPP region exhibits much lower emissions than in Figure 2.5. MEFs from Siler-Evans *et al.* are only for CO_2 instead of CO_2e, but that does not change general findings substantially.



(a) (b)

Figure 2.6 CO_2 emission savings based on NERC region-level marginal emission factors. These maps are analogous to Figure 2.5a and 2.5b which were based on NERC region-level average emission factors.

Sensitivity of results to energy prices

To assess the effect of energy prices, we ran four analyses: 1) 20 percent higher and lower electricity rate in each state, while natural gas price is kept at 2010 prices, and 2) 20 percent higher and lower natural gas price while electricity rate in each state are kept at 2010 prices. The

±20 percent range was chosen to cover historical changes of energy prices over the last 10 years. A decrease in natural gas prices reduces the size of HRE. Figure 2.7a and 2.7b show how a natural gas price decrease affects HRE. The map patterns are almost identical to Figure 2.2e and 2.2f, but with the scales shifted downward. Figure 2.7c and 2.7d illustrate a 20 percent increase in natural gas prices. The scenarios in Figure 2.8 illustrate the effect of electricity price changes, and highlight that a retrofit under a higher electricity price results in larger energy cost savings and smaller size of HRE. A 20 percent rate increase leads to about $10-20 additional savings per year depending on regions.

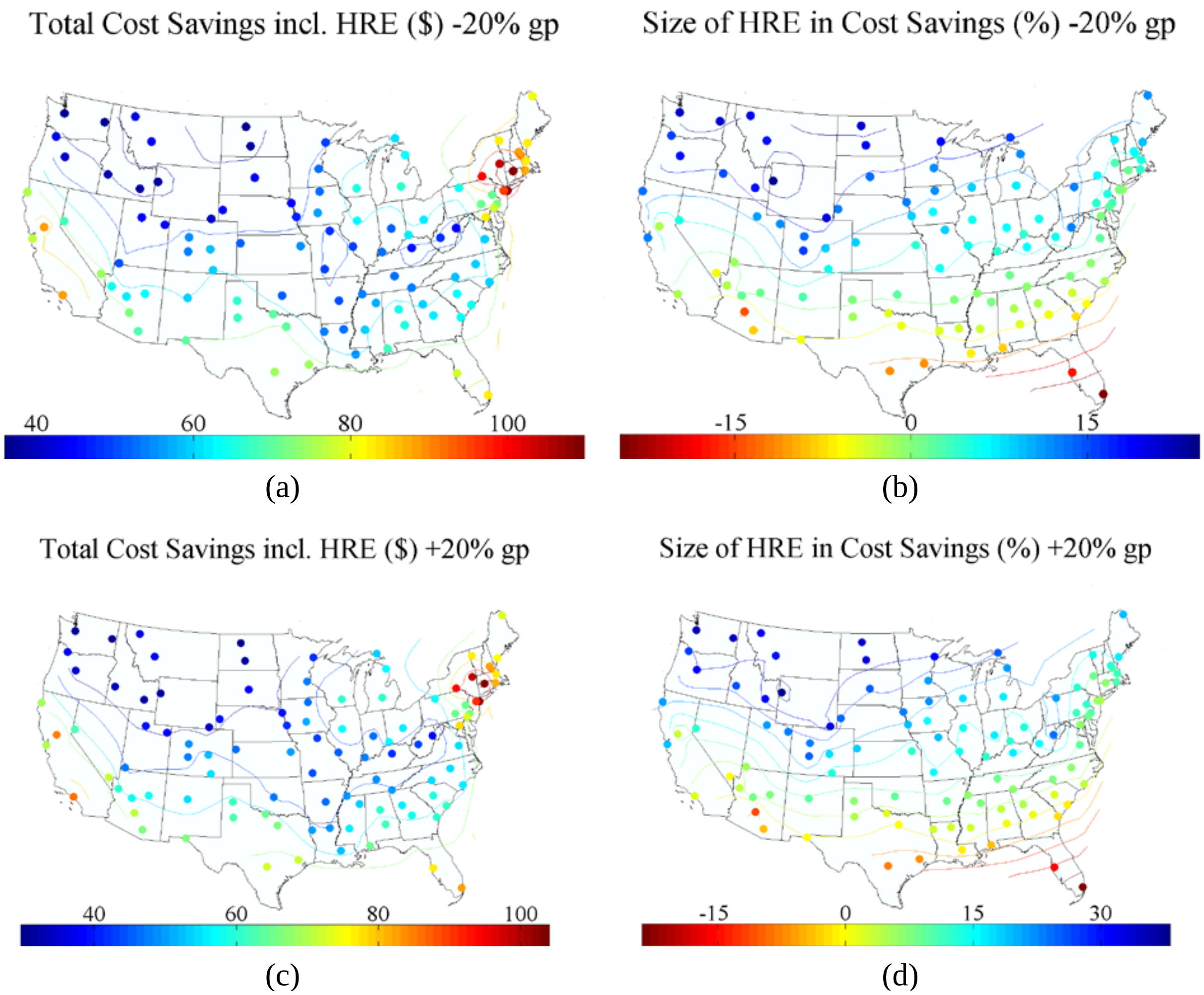


Figure 2.7 Sensitivity of energy cost savings to price change of natural gas. a) and b) are for 20 percent price decrease and c) and d) are for 20 percent increase. We see that patterns are almost identical, but the color bar ranges of c) and d) are for lower values than those of a) and b) because a higher natural gas price results in a bigger rebound effect due to HRE and thus in a more negative impact on energy expenditure savings. These figures can be compared with Figure 2.2e and 2.2f.

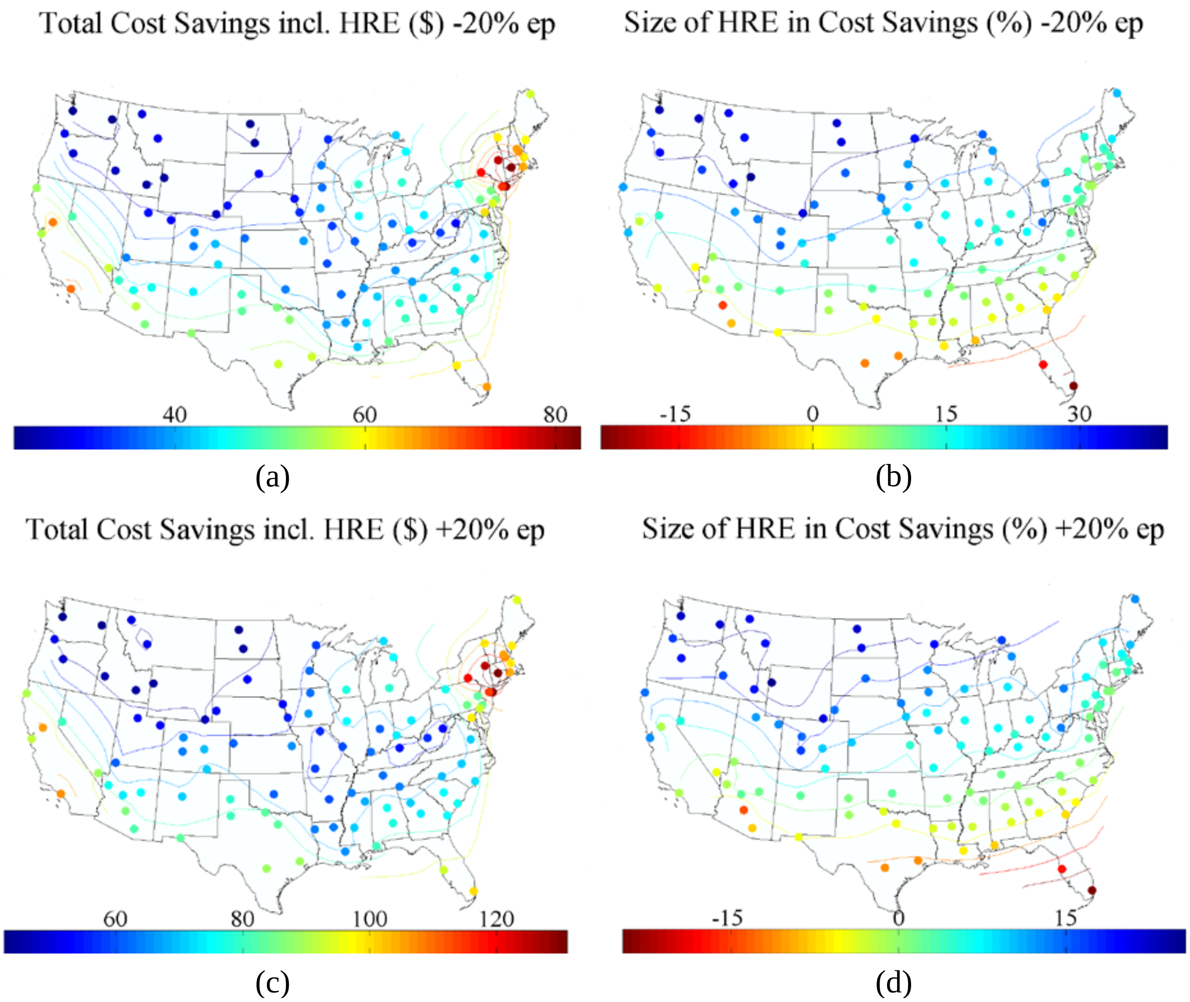


Figure 2.8 Sensitivity of energy cost savings to changes of residential electricity rate. a) and b) are for 20 percent price decrease and c) and d) are for 20 percent increase. A higher electricity rate in c) and d) results in larger electricity cost savings from a retrofit making the size of HRE relatively smaller.

Sensitivity of results to building orientation, wall insulation (R-values), occupancy, lighting consumption profile, and efficiency of heating and cooling equipment

The orientation of a building will affect the external heat gain from solar radiation, which in turn influences heating or cooling loads mainly during the daytime. In the results presented up to now, we assume the building is facing south. We test effects of buildings facing southwest and southeast.

For wall insulation, we test a range of R-values ranging from 50 percent to 120 percent of IECC 2009 levels used in our base-case assumptions above.

Different occupancy scenarios also affect internal heat gains and will change the size of HRE. In EnergyPlus, there are two factors determining internal heat gains from building occupancy: household size and daily occupancy profile. In the main simulation, the household size is assumed to be three, and the default occupancy schedule curve is shown as the solid line in Figure 2.9, which is adopted from Pacific Northwest National Laboratory's prototype input. We assume two extreme cases to see the impact of occupancy on HRE: 1) all family members present at home 24 hours/day, and 2) no one present between 7 am and 10 pm.

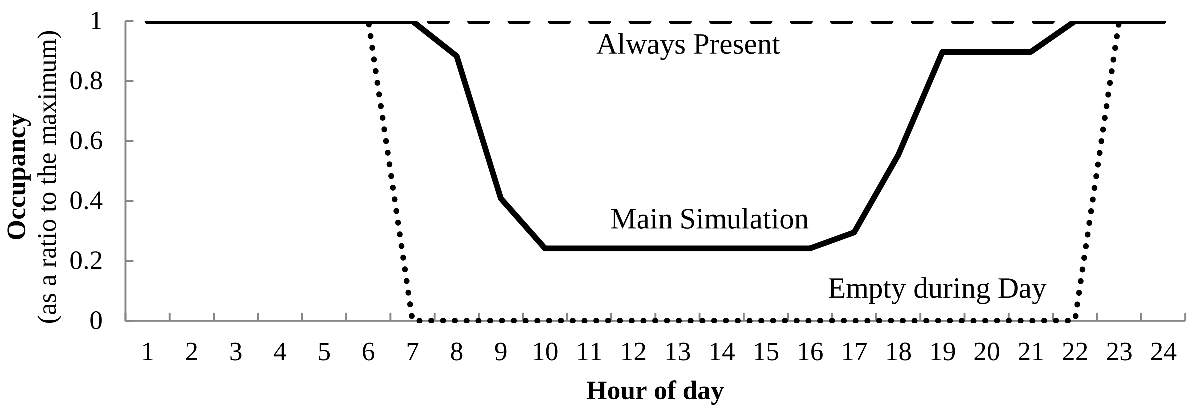


Figure 2.9 Occupancy profiles assumed in the base case and in the sensitivity analysis

Lighting usage patterns directly determine the lighting energy consumption and consequently the size of HRE. The consumption profile used in the main simulation is based on Hendron *et al.* (2010) and is shown in Figure 2.10 together with the two scenarios we used for our sensitivity analysis for a shorter and a longer day. The two scenarios were derived by changing the peaks of the original curve.

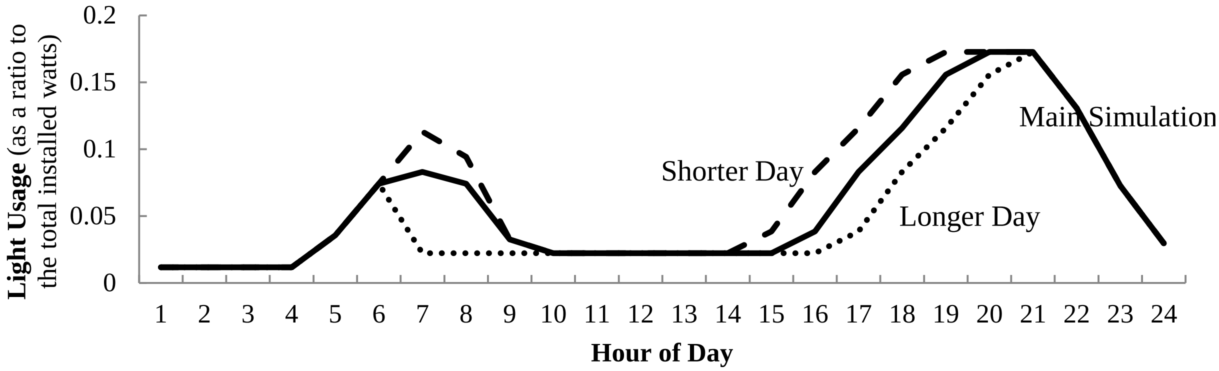


Figure 2.10 Lighting usage profiles assumed in the base case and in the sensitivity analysis

In addition, buildings with efficient heating equipment will get higher benefits from lighting retrofits. In the results presented so far, the gas furnace efficiency is 0.78 and the coefficient of performance of the central AC system is 4. For natural gas furnaces, usual annual fuel utilization efficiency values range from 0.55 to 0.95 (Canada Mortgage and Housing Corporation, 2008). For the central AC system we use a coefficient of performance ranging from 1.58 to 4.75, following the values from the California Energy Commission.[10]

We test the sensitivity of the main simulation results to the factors described so far for a city with a hot climate (Miami, FL) and a city with a cold climate (Caribou, ME). Among these five factors, simulation results are most sensitive to the efficiency of heating and cooling equipment. The other four assumptions did not substantially change the ratio between the intended savings (red line in Figure 2.11) and the final savings (blue bars) from the same ratio in the main simulation. For example, in Florida (Figure 2.11a), the size of HRE was +24 percent of intended savings in the main simulation (green bar). With a more efficient furnace and less efficient AC, which is expected to maximize HRE, HRE goes up to +57 percent (second bar) while with a low

[10] California Energy Commission (2006) Central Heating Ventilation and Air-Conditioning (HVAC) Systems. http://www.consumerenergycenter.org/residential/heating_cooling/heating_cooling.html

efficiency furnace it decreases to +20 percent (third bar). We are confident that results for real houses with diverse values of efficiencies of heating or cooling systems will vary within a reasonably limited range.

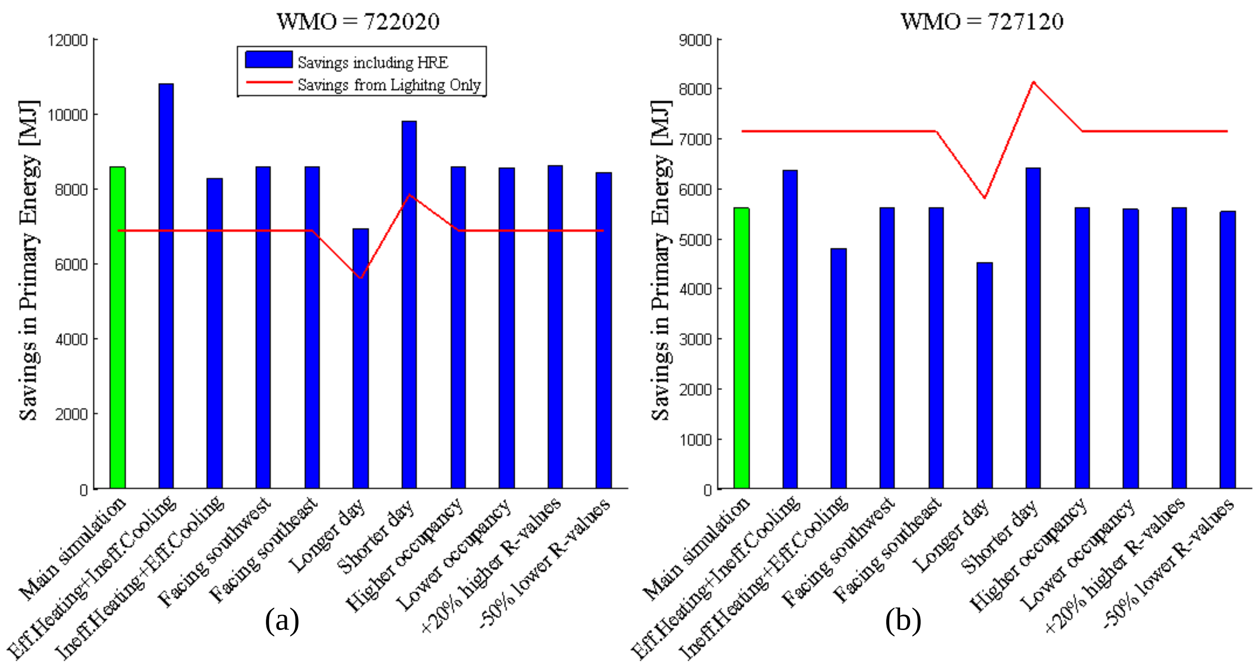


Figure 2.11 Sensitivity of primary energy savings to various factors in a) Miami, FL (722020) and b) Caribou, ME (727120). The red line shows the intended primary energy savings from lighting retrofit and blue bars are savings including HRE. The red lines are not constant because while all other scenarios assume identical savings from lighting, ‘longer (shorter) day’ scenarios assume more (less) lighting energy consumptions than the main simulation. This analysis assumes a gas furnace and slab foundation.

Sensitivity of results to lighting technology type

As LED light bulbs are expected to become more popular, we test the effect of adopting LEDs on the size of HRE. LED bulbs currently available in the markets are slightly more efficient than CFLs. For this analysis, we assume 80 lumen/watt and 60 percent heat dissipation rate for LEDs. The result in Figure 2.12 shows that the case with LEDs saves more electricity (i.e., the green bar on the right is lower than the green bar on the left) while the rebound (the yellow rectangles) due to HRE is also larger than the CFL case, because LEDs contribute less to space heating than

CFLs. When compared with the total primary energy consumption (the blue bar), the absolute sizes of HRE for both cases are very small, but between the two cases, overall energy savings are about 17 percent larger when LEDs are used. The sizes of HRE for the two cases are almost identical, which is 16 percent.

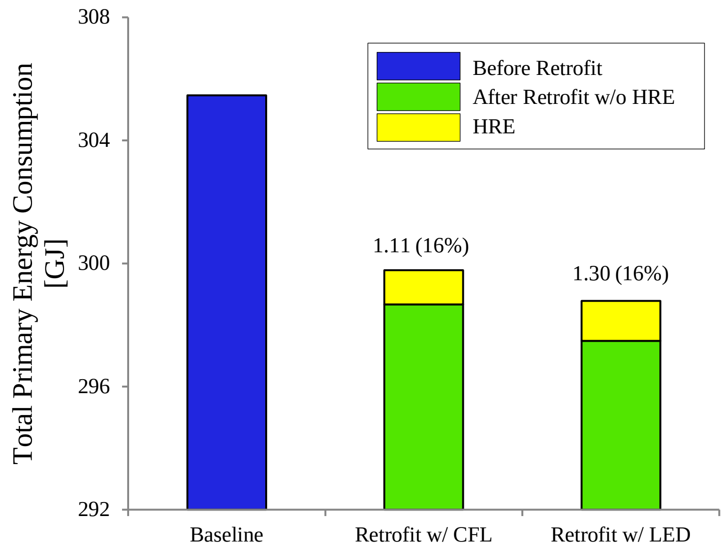


Figure 2.12 Effect of using LEDs instead of CFLs for replacement on total primary energy consumption in Bismarck, ND. The numbers on the bars show the size of HRE (yellow boxes) both in absolute terms (in GJ) and in relative terms. Note that the vertical axis starts from a nonzero value.

2.5. Conclusion and policy implication

In this work, we investigate the heat replacement effect of switching to more efficient lighting system on net primary energy consumption, CO_2e emissions, and savings in energy bills for single-family detached houses across the U.S.

Almost all cities achieve positive savings in all three aspects from the simulated lighting retrofit scenario when we account for heat replacement effects. However, in a few states, where the emission factors for electricity generation are very low (WA, ID, OR, and VT), the overall emissions associated with the building may not decrease as expected or actually increase as a result of the lighting efficiency measures. This suggests that as the U.S. electricity grid becomes less carbon intensive, these indirect effects associated with changes in heating and cooling demands may actually become more important.

Among the assumptions tested for sensitivity analyses, main heating fuel type and efficiency rate of the heating/cooling equipment are the factors that have significant effects on the size of HRE. This is because using electricity as a main heating fuel incurs a larger HRE rebound because of its larger primary energy conversion rate than natural gas. Also the efficiency rates of equipment directly determine how much energy has to be spent to compensate the heat loss from switching to efficient lighting. Thus, building codes and energy efficiency measures that coupled lighting and heating and cooling equipment simultaneously are key to avoid large heat replacement effects.

In addition, energy prices and emissions factors are also crucial factors directly influencing the size of HRE in energy cost savings and emissions savings respectively. The size of HRE is more sensitive to changes in electricity rate.

Finally, we also find that for moderate lighting efficiency interventions, the overall effect is small in magnitude, corresponding at most to around one percent of either total emissions or of energy consumption by a house.

Appendix

A2.1. Estimating HRE

Figure 2.13 illustrates the HRE from a lighting retrofit. The lighting retrofit is expected to reduce the three quantities of our interest (energy consumption, CO_2e emissions, and energy expenditure) from the baseline total $C_{baseline}$. When HRE is not considered, one expects that either energy consumption, CO_2e emissions, or energy expenditures would be reduced to level C_{noHRE} and therefore achieve a saving of a (=$C_{baseline}$ - C_{noHRE}), occurring solely from the difference in lighting energy consumptions before and after the retrofit. However, when HRE is taken into account, energy consumption, CO_2e emissions, or energy expenditure become instead C_{HRE}, because of changes in provision of heating and cooling energy services. The amount b can be either positive or negative depending on how much each end-use energy consumption changes.

The resulting HRE is computed as $b/a \times 100$. Thus, the interpretation can be similar to a rebound effect. We can refer to b also as absolute HRE or rebound size.

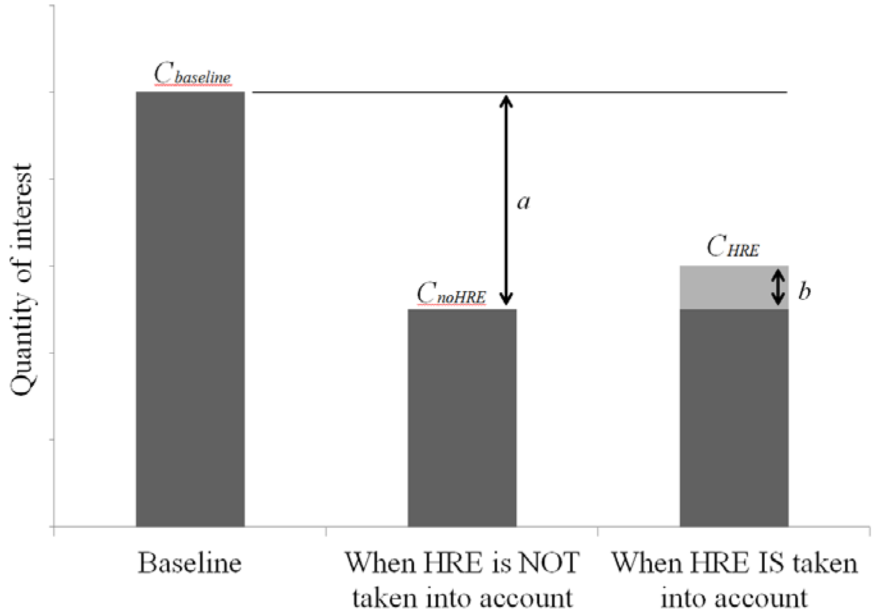


Figure 2.13 Example of the heat replacement effect (HRE). The *baseline* represents the total amount of energy consumption, CO_2e emission, or energy expenditures. The second bar in the figure shows the expected energy consumption, CO_2e emission, or energy expenditures after a lighting retrofit when HRE is not taken into account. The third bar shows the same quantities, but when HRE is accounted for (i.e. changes in the provision of heating and cooling services after the lighting retrofit). The size of HRE is given by $b/a \times 100$. A negative size of HRE indicates that the final saving with HRE incorporated (=a-b) is larger than what is anticipated (=a), while a positive HRE means that the final saving is less than what is anticipated.

A2.2. Maps of percent savings of primary energy, CO_2e emissions, and energy expenditures in scenarios with no HRE.

Figure 2.14 shows the percentage differences between the baseline and the efficiency scenarios for primary energy consumption, CO_2e emissions, and household energy expenditures for single-family detached houses with slab foundation and gas furnace in each of the 105 cities, without accounting for HRE. Lighting interventions that are aiming at compliance with IECC 2012 can lead to, at most, a four percent reduction at a building level in total household primary energy consumption, total CO_2e emissions, or energy expenditures. It is noteworthy that even when

HRE for lighting is large, we can anticipate that the effects in overall household energy consumption, emissions, or expenditures will be small.

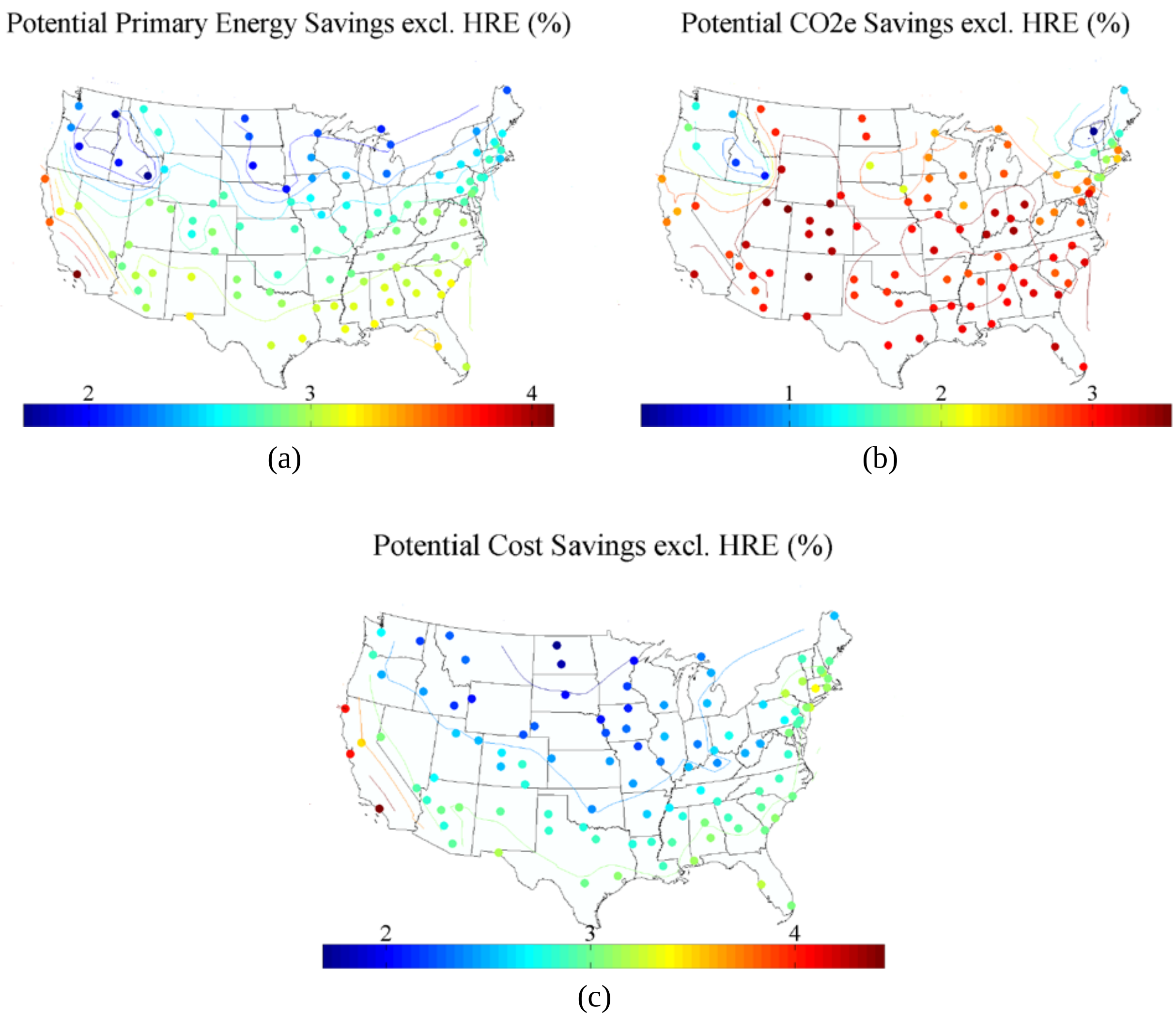


Figure 2.14 Percent savings for a) Primary energy consumption, b) CO_2e emission, and c) energy expenditure (natural gas and electricity) for single-family detached houses with slab foundation and gas furnace in each of the 105 cities when HRE is **<u>not</u>** included.

A2.3. Lighting baseline and efficiency scenarios

We constitute our baseline scenario based on Navigant Consulting (2012). It reports that in 2010 an average household living in a single-family detached house has 53 light bulbs installed in indoor spaces, among which 68 percent are incandescent, 24 percent are CFLs, and, 8 percent are linear fluorescent lamps (LFL). We ignored other types taking less than one percent in total. According to the report, average wattage per lamp is 47W and average floor space is 2,178 ft^2 for this residence type. Since luminous efficacy values for each light bulb type have a range of values, we pick representative values based on common items available in hardware stores. The values are 15, 55, 88 lumen/watt for incandescent lamps, CFLs, and LFLs respectively. We also adopt from the report the ratios of electricity consumed by each type of light bulbs. From these numbers, we obtain average illuminance level of 276 lm/m^2, average light power density of 12.2W/ m^2, and average wattage per incandescent lamp, CFL, and LFL of 59W, 17W, 33W respectively.

For the efficiency scenario, to be compliant with IECC 2012 lighting requirement, we assume the percentage composition of light bulb type changes to 25 percent incandescent bulbs, 67 percent CFLs, and 8 percent LFLs. Total number of bulbs, average illuminance, and average floor space are kept unchanged across the two scenarios. This assumption requires that incandescent bulbs with average 59W need to be replaced with 16W CFLs under our luminous efficacy assumptions to maintain the same illuminance level. Average wattage per bulb comes down from 47W to 28W, and average light power density becomes 7.4W/m^2 in this efficiency scenario.

A2.4. Type of foundation and heating systems for all single-family detached houses in the Residential Energy Consumption Survey (RECS) from 2009

In this study, we focus on single-family detached houses with slab foundation and gas furnace based on observations in the RECS 2009 data (U.S. EIA, 2009). Table 2.1 shows that 13.7 percent among 7,803 single-family houses observed in the RECS have such configurations.

Since the PNNL prototypes model only those buildings with four major types of foundations and heating systems, a large percent of RECS observations cannot be represented by these prototypes.

Table 2.1 Percentage of single-family detached houses with given heating equipment and foundation type (percentage in parenthesis)

		Foundation Type						
		Slab	Crawlspace	Unheated Basement	Heated Basement	Other	Mixed	Total
Heating Equipment Type	No Heating	99 (1.3%)	45 (0.6%)	3 (0.0%)	0 (0%)	18 (0.2%)	16 (0.2%)	181 (2.3%)
	Gas Furnace	**1,066 (13.7%)**	457 (5.9%)	384 (4.9%)	713 (9.1%)	82 (1.1%)	872 (11.2%)	3,574 (45.8%)
	Oil Furnace	6 (0.08%)	19 (0.2%)	76 (1.0%)	70 (0.9%)	1 (0%)	82 (1.1%)	254 (3.3%)
	Elec. Resistance	731 (9.4%)	278 (3.6%)	70 (0.9%)	110 (1.4%)	103 (1.3%)	206 (2.6%)	1,498 (19.2%)
	Elec. Heat Pump	333 (4.3%)	178 (2.3%)	30 (0.4%)	54 (0.7%)	15 (0.2%)	110 (1.4%)	720 (9.2%)
	Other	221 (2.8%)	318 (4.1%)	283 (3.6%)	243 (3.1%)	68 (0.9%)	443 (5.7%)	1,576 (20.2%)
	Total	2,456 (31.5%)	1,295 (16.6%)	846 (10.8%)	1,190 (15.4%)	287 (3.7%)	1,729 (22.3%)	7,803 (100%)

3. Understanding how labeling affects choice for energy efficient light bulbs using a conjoint choice experiment

[This chapter has already been published in *Ecological Economics*:

Jihoon Min, Inês L. Azevedo, Jeremy Michalek, Wändi Bruine de Bruin, Labeling energy cost on light bulbs lowers implicit discount rates, Ecological Economics, Volume 97, January 2014, Pages 42-50.]

3.1. Introduction

In 2008, residential compact fluorescent lamp (CFL) socket saturation[11] was 10% nationwide (D&R International, 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, 2012), 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

[11] 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.

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; Golove and Eto, 1996; Brown, 2001), 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 Academy of Sciences on "America's Energy Future" (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, 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 Section 3.3 and 3.4 respectively, and in Section 0 we conclude.

3.2. 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 3.1 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:

$$U_j = -\beta_1 \cdot OCost_j - \beta_2 \cdot Price_j - \beta_3 \cdot Discomfort_j + \varepsilon_j \tag{3.1}$$

Where U_j is the utility gained by selecting product j, $OCost_j$ is the annual electricity cost (\$/yr) 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 ε_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 β_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:

$$\hat{\beta}_2 = \hat{\beta}_1 \frac{r(1+r)^q}{(1+r)^q - 1} \tag{3.2}$$

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

Table 3.1 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 Harman (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 National Lab	1982	0% ~ 400%	Econometric model (Discrete choice analysis)
Mau et al. (2003)	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)

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 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.

3.3. Methods

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*.

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,[12] using laptops set up with choice tasks (using Sawtooth software) and a survey.[13] 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 Figure 3.1.

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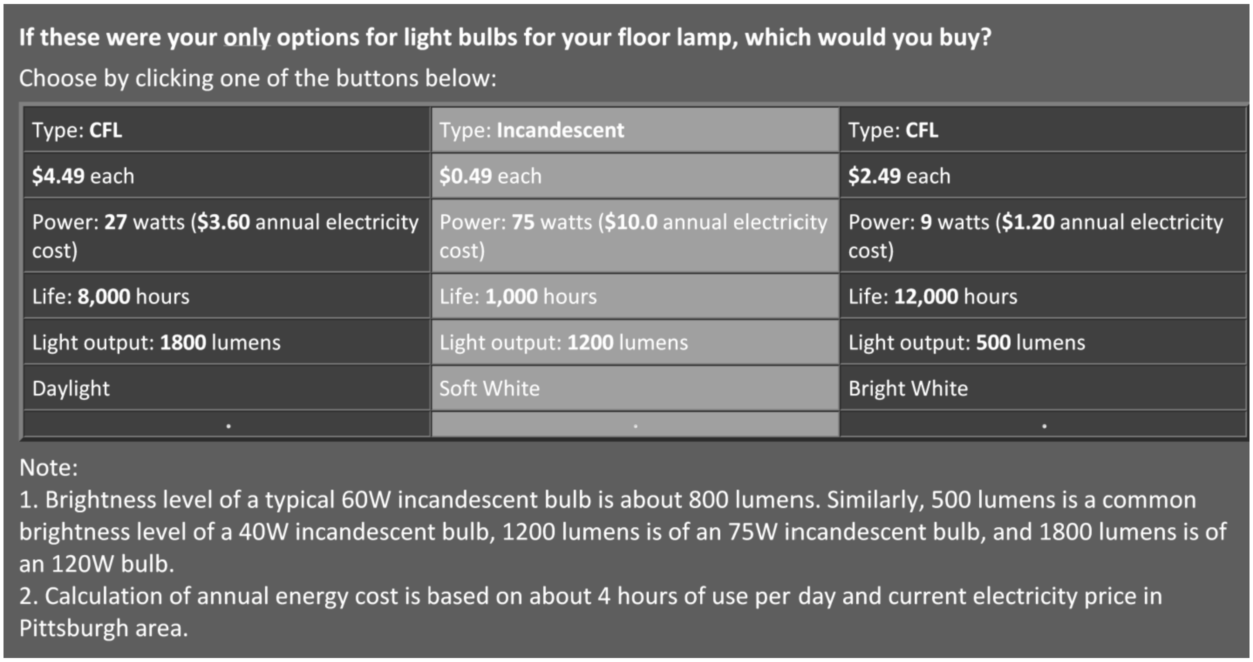
[12] The Center for Behavioral and Decision Research (http://www.cbdr.cmu.edu/datatruck/index.html)

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



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.

Figure 3.1 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.

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 × 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.: 75W CFL with a 1,000 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 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.

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.

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.

Analytical model

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.[14] 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.[15] The utility U_{ij} that consumer *i* draws from product alternative *j* is modeled as:

$$U_{ij} = V_{ij} + \epsilon_{ij} = \sum_{k=1}^{K} \left(\beta_k \cdot x_{ijk} + \sum_{n=1}^{N} \gamma_{kn} \cdot z_{in} \cdot x_{ijk} \right) + \epsilon_{ij}, \tag{3.3}$$

[14] 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 SP1 and Model SP2 in Table 3.3).

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

where β_k is the preference coefficient for attribute k, x_{ijk} is the k-th attribute of alternative j subject i's choice task, γ_{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 ϵ_{ij} is the random error term, taken as an independent and identically distributed (i.i.d.) standard Gumbel distribution (Train, 2003). The interaction terms $z_{in} \cdot x_{ijk}$ reveal how individual characteristics can affect preference for bulb attributes. We assume continuous numerical bulb attributes unless otherwise noted, as shown in Table 3.2 below. For the mixed logit model, both β_k and γ_{kn} are random variables, assumed to be normally or log-normally distributed with distributional parameters estimated via likelihood maximization.

Specifically, our base model (Model SP2 in Table 3.3), which excludes respondent covariates z_{in}, is:

$$
\begin{aligned}
U_{ij} = {} & (\bar{\beta}_1 + \sigma_1 \nu_{1i}) x_{ij}^{\mathrm{TYPE}} - \exp(\bar{\beta}_2 + \sigma_2 \nu_{2i}) x_{ij}^{\mathrm{PRICE}} + \exp(\bar{\beta}_3 + \sigma_3 \nu_{3i}) x_{ij}^{\mathrm{LIFE}} \\
& + (\bar{\beta}_4 + \sigma_4 \nu_{4i}) x_{ij}^{\mathrm{BRIGHT}} + (\bar{\beta}_5 + \sigma_5 \nu_{5i}) \left(x_{ij}^{\mathrm{BRIGHT}}\right)^2 + (\bar{\beta}_6 + \sigma_6 \nu_{6i}) x_{ij}^{\mathrm{WATT}} \\
& + \sum_{m=1}^{2} (\bar{\beta}_{7m} + \sigma_{7m} \nu_{7mi}) x_{mij}^{\mathrm{COLOR}} \\
& + D_i^{\mathrm{OPCOST}} \Big(\bar{\beta}_1^{\mathrm{C}} x_{ij}^{\mathrm{TYPE}} + \bar{\beta}_2^{\mathrm{C}} x_{ij}^{\mathrm{PRICE}} + \bar{\beta}_3^{\mathrm{C}} x_{ij}^{\mathrm{LIFE}} + \bar{\beta}_4^{\mathrm{C}} x_{ij}^{\mathrm{BRIGHT}} + \bar{\beta}_5^{\mathrm{C}} \left(x_{ij}^{\mathrm{BRIGHT}}\right)^2 \\
& + \bar{\beta}_6^{\mathrm{C}} x_{ij}^{\mathrm{WATT}} + \sum_{m=1}^{2} \bar{\beta}_{7m}^{\mathrm{C}} x_{mij}^{\mathrm{COLOR}} \Big) + \epsilon_{ij},
\end{aligned}
\tag{3.4}
$$

where m indexes the discrete levels of the color attribute, $\bar{\beta}$ and σ are the distributional parameters for the random coefficients, ν is a random variable with an i.i.d. 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 SP3 in Table 3.3), 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 towards climate change, toxicity associated with certain lighting technologies, participants' awareness of the relationships between bulb characteristics, and participants' political orientation.

Table 3.2 Descriptions of variables

Variable	Description	Value
x_{ij}^{TYPE}	Dummy indicating bulb type	0: incandescent, 1: CFL
x_{ij}^{PRICE}	Price of the bulb *j* in subject *i*'s choice task	\$0.49 / \$2.49 / \$4.49
x_{mij}^{COLOR}	Dummy for color, where x_{1ij}^{color} is bright white and x_{2ij}^{color} is daylight	0: No, 1: Yes
x_{ij}^{LIFE}	Lifetime of the bulb *j* in subject *i*'s choice task	1,000/8,000/12,000 [hours]
x_{ij}^{BRIGHT}	Brightness level of the bulb *j* in subject *i*'s choice task	500/1,200/1,800 [lumens]
x_{ij}^{WATT}	Power consumption of the bulb *j* in subject *i*'s choice task	9/25/75 [watt]
D_{i}^{OPCOST}	Dummy indicating whether annual operating cost information is provided to subject *i*	0: No, 1: Yes
$z_{i}^{\text{EXPERIENCE}}$	Dummy indicating whether subject *i* has used CFLs before	0: No, 1: Yes
z_{i}^{BUYBULB}	Dummy indicating whether subject *i* buys light bulbs sometimes	0: No, 1: Yes
z_{i}^{HEALTH}	Dummy indicating whether subject *i* has experienced any health issues related to CFL use	0: No, 1: Yes
z_{i}^{BACHELOR}	Dummy indicating whether subject *i* has a bachelor's degree	0: No, 1: Yes
z_{i}^{MIDINC} z_{i}^{HIINC}	Dummy indicating subject *i*'s annual household income, where mid-income is between \$30k and \$75k and high-income is above \$75k	0: No, 1: Yes
z_{i}^{TOXICCFL}	Dummy indicating whether the subject believes only CFLs contain toxic materials	0: No, 1: Yes
$z_{i}^{\text{TOXICBOTH}}$	Dummy indicating whether the subject believes both bulbs contain toxic materials	0: No, 1: Yes
$z_{i}^{\text{TOXIC,k}}$	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
$z_{i}^{\text{KNOWLEDGE}}$	Number of correct answers among the four questions regarding basic lighting technology	0-4
$z_{i}^{\text{CC,k}}$	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}^{LIBERAL}	Dummy indicating whether the subject is politically liberal	0: No, 1: Yes

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

$$\text{(annualized capital cost)} = \frac{r(1+r)^{x^{\text{LIFE}}}}{(1+r)^{x^{\text{LIFE}}}-1} \cdot x^{\text{PRICE}}. \tag{3.5}$$

Here, x^{LIFE} is expressed in years.[16] The base model specification for estimating IDR is

$$\begin{aligned} U_{ij} = -exp(\beta_0 + \sigma_0 \nu_{0i}) \left(\frac{\beta_1 (1+\beta_1)^{x_{ij}^{\text{LIFE}}}}{(1+\beta_1)^{x_{ij}^{\text{LIFE}}}-1} x_{ij}^{\text{PRICE}} + x_{ij}^{\text{OPCOST}} \right) + (\beta_2 + \sigma_2 \nu_{2i}) x_{ij}^{\text{TYPE}} \\ +(\beta_3 + \sigma_3 \nu_{3i}) x_{ij}^{\text{BRIGHT}} + (\beta_4 + \sigma_4 \nu_{4i}) \left(x_{ij}^{\text{BRIGHT}}\right)^2 \\ + \sum\nolimits_{m=1}^{2} (\beta_{5m} + \sigma_{5m} \nu_{5mi}) x_{mij}^{\text{COLOR}} + \epsilon_{ij}, \end{aligned} \tag{3.6}$$

where β_0 represents average consumer sensitivity to annualized cost of ownership and β_1 represents the consumer's IDR. Other βs can be interpreted in the same way as in Equation (3.4).[17,18] Through maximum likelihood estimation, we can estimate the population's average

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[16] We assume that consumers accept the lifetime information written on packages as true, i.e. they do not anticipate a defective bulb failing earlier than the rated lifetime. However, the rated lamp life is the point at which 50% of given products have failed, which means that some bulbs will still fail earlier than the rated life.

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

IDR (i.e. $\hat{\beta}_1$) employed when making purchasing decisions for any lighting products. Because the conjoint task is randomized and the attributes given in the task are independent from each other, the IDR estimated from the model above will be independent of the presence of other model covariates.

3.4. Results and Discussion

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.

Figure 3.2 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 $10k appear over-represented. Median tiers for income, education, and age were $30-50k per year, bachelor's degree, and age group 25-34. 56% of participants were male, 41% owned their houses, and 17% have children.

[18] 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.

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 $\succ$ Price $\succ$ Lifetime $\succ$ Energy Cost $\succ$ Color $\succ$ Wattage $\succ$ Type $\succ$ Wattage Equivalent $\succ$ Time to Full Brightness $\succ$ Shape.

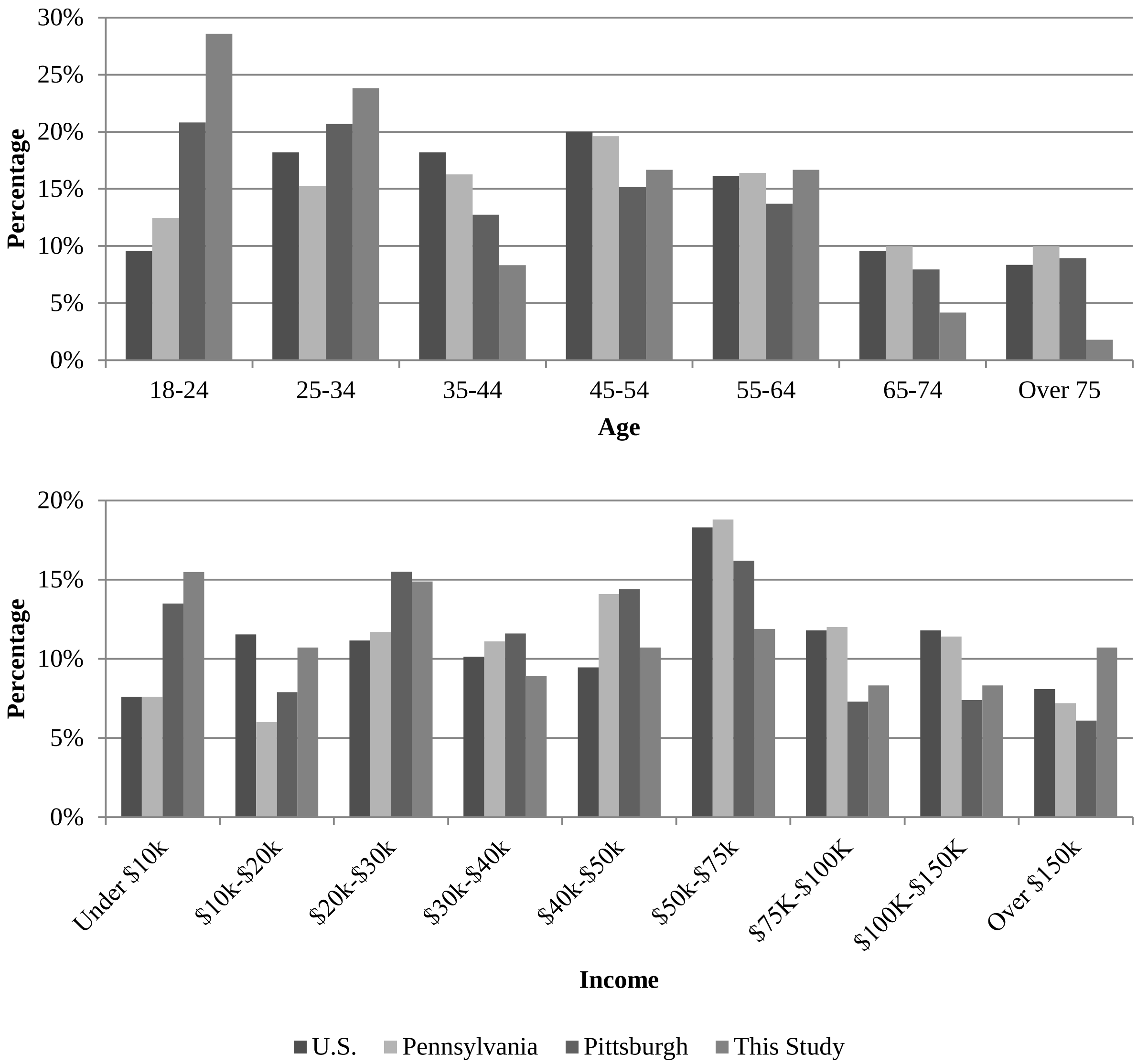

Figure 3.2 Distributions of age and income (N=168). City and state data are from the 2010 U.S. Census (U.S. Census Bureau, 2010).

Main results

Table 3.3 shows our main results. Models 1 and 2 show the results for a model that does not include consumer specific attributes, while Model SP3 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 β^{X} and β^{PRICE}. However in our case, since many β^{X} values and β^{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*.[19]

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

Table 3.3 Main model results

	VARIABLES	Model SP1 $\bar{\beta}$	Model SP2 $\bar{\beta}$	Model SP2 σ	Model SP3 $\bar{\beta}$	Model SP3 σ
Main effects of bulb attributes	CCT=3700K	-0.141 (0.0796) *	-0.140 (0.120)	0.678 (0.112)***	-0.147 (0.120)	0.679 (0.106)***
	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(x10^3 lumens)	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(x10^3 hours) (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)*(toxicity in CFL)*(toxic=not very dangerous)				-0.347 (0.360)	
	(Type=CFL)*(toxicity in CFL)* (toxic=somewhat dangerous)				0.506 (0.332)	
	(Type=CFL)*(toxicity in CFL)* (toxic=very dangerous)				-0.806 (0.480)*	
	(Type=CFL)*(toxicity in CFL)* (toxic=not aware)				-0.870 (0.810)	
	(Type=CFL)*knowledge				-0.0518 (0.0897)	
	Watt*Basic knowledge				-0.000954 (0.00147)	
	(Type=CFL)*Liberal				0.370 (0.200)*	
	Watt*Liberal				-0.00746 (0.00329)**	
	Observations	6,552	6,552		6,552	
	Log-Likelihood	-2,164	-1,936		-1,921	
	AIC/BIC	4361/4470	3920/4083		3925/4210	

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

Analysis

3.4.1 How do bulb-specific factors affect consumer choices?

From Model SP2, 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 1,000 hours of lifetime increase within the range tested in the experiment (1,000 ~ 12,000 hours), and that amount increased by $0.14 when they were shown annual cost estimates. They are willing to pay $0.46 more for every 10W decrease within the range of 9~75W when the annual cost information is shown.

3.4.2 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 SP2 and Model SP3 in Table 3.3, 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.

3.4.3 What is the right level of model complexity for policy analysis and for energy models?

Table 3.3 presents the three models we test for this analysis. Among them, the MNL model (Model SP1) is the simplest and the easiest to understand, but it has the highest AIC/BIC (Akaike Information Criterion / Bayesian Information Criterion) values and the smallest likelihood value compared to the other two models, suggesting that the fit of Model SP1 to the observed data is relatively poor when compared with the others.[20] A likelihood ratio test between Model SP1 and Model SP2 gives $\chi^2(8)=457.1$ and $p<0.001$, while a similar test between Model SP2 and Model SP3 gives $\chi^2(18)=30.8$ and $p=0.03$. Combining together 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 SP2 addresses choice complexity and has the benefit of modeling consumer heterogeneity and avoiding the restrictive substitution patterns (i.e. IIA).

3.4.4 How does disclosing annual operating cost information impact choices?

Model SP2 and Model SP3 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 SP2, and holding all other attributes constant, when the operating cost information was given a consumer was willing to pay \$0.14 more for a 1,000-hour increase of lifetime and \$0.46 more for a 10W 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[21] The fact that lower power and longer lifetime affect consumer choices less when operating cost information is not shown is

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[20] AIC/BIC values are commonly used measures for selecting econometric models based on trade-offs between model complexity and goodness of fit. Smaller AIC/BIC values indicate better models.

[21] 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.

a potential reason why CFLs have underperformed in the market prior to introduction of packaging labels that incorporate operating cost estimates.

3.4.5 What are the implicit discount rates (IDR) that consumers use when making choices for lighting technologies?

We fit a nonlinear model as shown in Equation (3.6) 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 3.4. 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.

Table 3.4 Estimates of implicit discount rates depending on income level and the availability of operation cost information.

Implicit discount rates	Income level Low (below $30k/yr)	 Middle ($30k-75k/yr)	 High (over $75k/yr)	Overall
Operating cost shown	182% (38%)	57% (19%)	36% (35%)	100% (22%)
Operating cost not shown	764% (315%)	491.2% (49.2%)	203% (73%)	560% (70%)

Note: standard errors in parentheses

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 Equation (3.6) 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 3.4 suggest that consumers are pessimistic about (or pay little attention to) future economic savings delivered from the energy efficient 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.

3.4.6 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 SP2, 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.[22] In Table 3.5, 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.

Table 3.5 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 Figure 3.2.

		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%

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

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 3.6.

Table 3.6 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%

In Table 3.7, we compare the results from estimates of choices using Model SP2 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. *EAL_perfect* is EAL when all estimated shares are assumed to be equal to the true shares (i.e. perfect aggregate model).

- *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, brand, etc. 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.

Table 3.7 Estimation statistics calculated for the three types of data with Model SP1. 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. EAL_perfect is EAL when all estimated shares are assumed to be equal to the true shares (i.e. perfect aggregate model).

	Estimation data		Compensation task		Physical choice	
	Model	Random	Model	Random	Model	Random
Log-likelihood	-1936	-2399	-173.0	-184.6	-243.5	-270.4
Equivalent average likelihood (EAL)	41.2%	33.3%	35.3%	33.3%	23.5%	20.0%
EAL_perfect			35.7%		25.0%	
Average hit rate (AHR)			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	

3.5. 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 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. 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 IDRs were observed to decrease as household income increases. This 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.

Appendix

A3.1. Field experiment setup and procedure

Experiment setup

The experiment was performed over the course of three days in Carnegie Mellon University's data truck at a neighborhood in Pittsburgh. Participants were recruited through word-of-mouth on the street. Participants were asked to sign on the consent form first and given a brief introduction about the experimental process. Then they were shown a display of three different lights with different color temperatures, with the respective color names, "daylight" / "soft white" / "bright white" (Figure 3.3). The display was presented because from the pilot tests we learned that consumers might not know how this taxonomy, used in the labels, may actually correspond to different light color. The lamps were left on near the participants, so that they were able to look at the color of the light while responding to the survey if needed.

Figure 3.3 Displays of three different light colors used in the choice experiment

Experiment Procedure

After this, participants were invited to answer several questions using laptops. Total number of questions was 39 (15 choice tasks + 24 additional questions). Time spent for the whole process per participant is about 20-25 minutes. In the experiment truck, seven laptops were installed to accommodate several subjects at the same time: three for with-cost group (containing questions including the annual operating cost information) and the other four for without-cost group. Participants were seated at a random laptop while the balance between the numbers of people in with-and without-cost groups was maintained.

Compensation

Compensation for participants was devised as follows. Jointly with the consent form, participants were given an instruction page where it was stated that "*Your choice from one specific question, placed randomly among the fifteen, 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 (Figure 3.2). The compensation bulb would be the one that is the most similar to the choice made in the compensation task.

Procedure to compare choices from the computer-choice experiment with real light bulb choices

Once the choice computer-based 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 packages (Figure 3.4). Information was also provided on the price of those lamps on a tag next to the lamp package. Each participant was asked to select one of these lamps as compensation for her participation in the experiment.

Summary of experiment procedure

1. A participant signs on the consent form after an experimenter explains the experiment and the compensation procedure.
2. The participant is shown 3 lamps of different color temperatures to familiarize herself with the taxonomy (“daylight” / “soft white” / “bright white”).
3. The participant is seated in front of a laptop.
    a. The introduction page shows pictures of incandescent lamps and compact fluorescent lamps and also pictures of different light colors.
    b. The participant answers 15 choice tasks. Each choice task screens provides the following information at the bottom of the screen:
        i. *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.*
        ii. *Calculation of annual energy cost is based on about 4 hours of use per day and current electricity price in Pittsburgh area.*
4. After finishing the choice tasks, the participant is walked by the experimenter to a table on which the five types of light bulbs are placed (Figure 3.4). The participant is asked to pick one that they are to take home.
5. The participant returns to his laptop and continue answering the remaining survey questions.

6. After a participant finishes all the tasks from the computer, the experimenter determines which choice the participant made in computer-based compensation task and hands out the chosen light bulbs.

Figure 3.4 Choice experiment with real light bulb packages. At the experimental setup, five types were presented to the subjects.

A3.2. Details on preparatory steps and pilot surveys

In order to secure external validity of the experiment, we performed a series of preliminary interviews and surveys before designing the main study, This was done to assess what are the main factors stated by consumer when performing choices towards lighting technologies. For this purpose, we performed the two following tasks:

Online open-ended question

We asked users of Amazon Mturk (www.mturk.com) the following question: "*What are the five most important factors that you would consider when purchasing a light bulb for your living room*?" This web application connects anonymous people online with those who want to get their tasks done by those anonymous users. In total, 50 people participated, and the most frequently mentioned factor was price followed by energy use (or energy efficiency). The results are shown in Figure 3.5. Since this study only deals with general-purpose light bulbs and is neutral to brands, brand and socket type are not included in the experiment. We chose the top six factors (price, energy use, wattage, color, lifetime, and brightness) as the attributes to be used in the field experiment. Energy use and wattage are shown separately in the graph because participants can mean brightness, energy consumption, or both by specifying wattage as an answer. These six important factors match with results from a previous survey by a light bulb manufacturer on light bulb preferences (Sylvania, 2013). The six most important factors reported in this survey were brightness, life, energy consumption, price, brand (where it is made), and color, ordered by rank. The seventh was whether the bulb has the Energy Star logo, and the eighth was dimmability, which we did not include in our experiment.

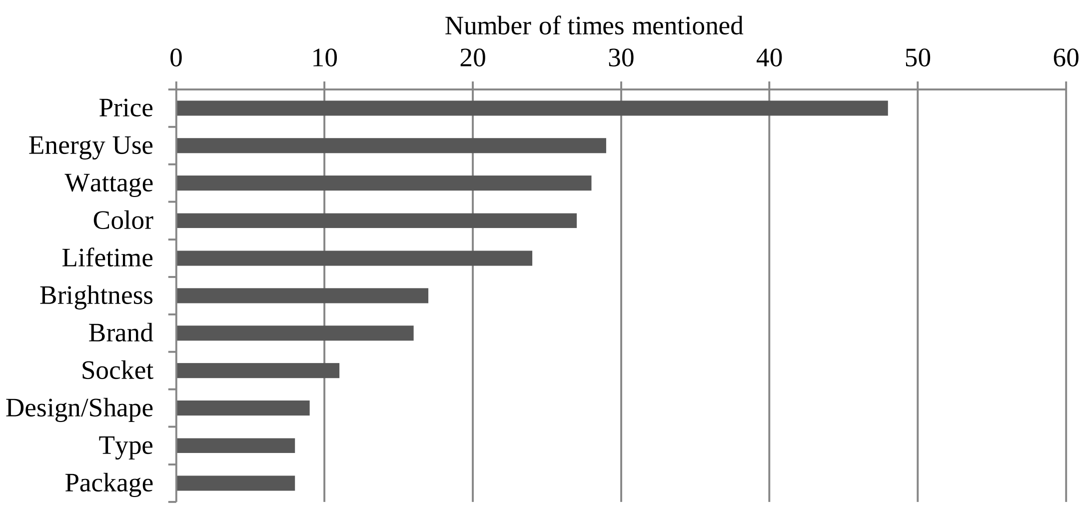

Figure 3.5 Important factors considered when purchasing a light bulb. Fifty people answered the question and each participant selected five factors. We use the top six factors in our experiment design.

Consumer interviews

We approached and interviewed eleven customers who picked general-purpose light bulbs in a hardware store. Eight of them chose incandescent bulbs and mentioned lack of experience with CFLs, headache experience with CFLs, faster starting time, lower price, and better color of incandescent bulbs for the main reasons of their choices. On the other hand, three of them chose CFLs and mentioned longer lifetime and lower operating cost for their main reasons. Based on these opinions, we added questions about health issues in the survey and included starting time as another item in the ranking question.

A3.3. Questionnaire for the field experiment

This is the exact text of the questionnaire provided to the participants. All these questions including the introductory paragraphs and images below are shown on laptop screens. There are fifteen repetitions of choice tasks like the one shown in Figure 3.2. The simplified table in the next page represents the fifteen choice tasks. Basic demographic questions are omitted because they follow general demographic question wording.

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1. **Choice Experiment**

Imagine you are a consumer wanting to purchase a light bulb for the general purpose of illuminating your living room.

You will be provided with information on three different kinds of bulbs and asked to select the one you like most. Please note that the questions may look similar, but attributes of the bulbs vary for each question. When answering the questions, please assume that the light bulbs are all currently available in the market.

The pictures below will help you answer the questions by showing the differences between the types and colors of each light bulb. If necessary, you can click on the pictures to keep them open in separate windows while answering the questions.

The entire survey should take about 20-30 minutes.

Based on your responses to this questionnaire, you will receive a set of light bulbs for compensation for participation.

Set #	Bulb #1	Bulb #2	Bulb #3
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			

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 a 75W incandescent bulb, and 1800 lumens is of a 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.

2. Experience and Awareness

Have you used energy-saving light bulbs (CFL: compact fluorescent light) at home before?

○	○
Yes	No

Do you sometimes purchase light bulbs?

○	○
Yes	No

Have you experienced mental or physical health-related issues due to lighting?
(If you have, please note what you experienced.)

- ○ Yes, I have experienced ____.
- ○ No

What is roughly the unit price you pay for electricity at home (in cents per kilowatt-hour)?

- ○ 1-5 cent/kWh
- ○ 5-10 cents/kWh
- ○ 10-15 cents/kWh
- ○ 15-20 cents/kWh
- ○ Over 20 cents/kWh
- ○ I don't know.

Do you believe any light bulbs contain toxic material?

- ○ Incandescent bulbs contain toxic material.
- ○ CFLs (compact fluorescent lights) contain toxic material.
- ○ Both contain toxic material.

- ○ None of them contain toxic material.
- ○ I don't know.

If you answered that certain light bulbs contain toxic material, how dangerous do you consider them to be? (Please select "Not applicable" if you selected "I don't know" or "None of them contain toxic material" in the previous question.)

- ○ Not at all dangerous
- ○ Not very dangerous
- ○ Somewhat dangerous
- ○ Very dangerous
- ○ Not aware
- ○ Not applicable

The issue of global climate change has been the subject of public discussion over the last few years. How serious do you consider the threat of global climate change is to us and our society?

- ○ Not at all serious
- ○ Not very serious
- ○ Somewhat serious
- ○ Very serious
- ○ Not aware

Which do you believe is the correct statement about climate change?

- ○ There is a lot of disagreement among scientists about whether or not global warming is happening.
- ○ Climate change is caused mostly by human activities.
- ○ None of these statements are correct.

For a traditional incandescent bulb, what do you think the relationship is between the wattage and the brightness of a light bulb?

- ○ The higher the wattage, the brighter the bulb.
- ○ The higher the wattage, the dimmer the bulb.
- ○ The two attributes are not related.

For a traditional incandescent bulb, what do you think the relationship is between a light bulb's wattage and your annual electricity bill?

- ○ A higher-wattage bulb is likely to give you a higher electricity bill.
- ○ A higher-wattage bulb is likely to give you a lower electricity bill.
- ○ The two attributes are not related.

What do you think the relationship is between a light bulb's wattage and its lifetime?

- ○ A higher-wattage bulb lasts longer than a lower-wattage bulb.
- ○ A higher-wattage bulb last shorter than a lower-wattage bulb.
- ○ The two attributes are not related.

Please select the statement that you believe is true.

- ○ CFLs (compact fluorescent lights) generally last longer than incandescent bulbs.
- ○ Incandescent bulbs generally last longer than CFLs (compact fluorescent lights).
- ○ CFLs and incandescent bulbs have a similar lifetime.

Which physical quantity does the *lumen* measure?

- ○ Energy use
- ○ Color
- ○ Temperature
- ○ Brightness
- ○ I don’t know.

Listed below are statements about the relationship between humans and the environment. Please indicate the degree to which you agree with each item. Choose the number of your response for each statement using the following scale: 1 = strongly disagree, 2 = mildly disagree, 3 = unsure, 4 = mildly agree, or 5 = strongly agree.

- The balance of nature is very delicate and easily upset.

○	○	○	○	○
1	2	3	4	5

- When humans interfere with nature, it often produces disastrous consequences.

○	○	○	○	○
1	2	3	4	5

- Humans are severely abusing the environment.

○	○	○	○	○
1	2	3	4	5

- The so-called "ecological crisis" facing humankind has been greatly exaggerated.

○	○	○	○	○
1	2	3	4	5

- If things continue on their present course, we will soon experience a major environmental catastrophe.

○	○	○	○	○
1	2	3	4	5

Please rank the following factors according to which you consider most important when purchasing a light bulb for general illumination purposes in your living room. (most important = 1, least important = 9)

☐	☐	☐	☐	☐	☐	☐	☐	☐
Brightness	Type	Price	Color	Wattage	Lifetime	Shape	Energy Cost	Time to Full Brightness

4. Understanding trends in efficient lighting adoption across the United States

4.1. Introduction

Many studies acknowledge that U.S. residential lighting sector consumes significant amount of electricity, but their consumption estimates do not necessarily concur with each other. For example, the two most recent reports from U.S. Department of Energy provide substantively different estimates. The first report, commissioned to Navigant Consulting, estimates that total residential lighting was 175TWh in 2010, 19% of total U.S. electricity consumption (Navigant Consulting, 2012), while another study, commissioned to DNV KEMA, reports 194TWh in the same year (DNV KEMA, 2012). The difference comes from distinct estimates of daily hour of use or number of lamps per home. Recent versions of Annual Energy Outlook (AEO) provide other sources of estimates. The AEO's are reports published by the Energy Information Administration that provide forecasted and historical consumption and prices for energy quantities. The estimates for total residential lighting electricity consumption for year 2010 are 211, 208, 202, and 190TWh in the AEOs 2010, 2011, 2012, and 2013, respectively. (U.S. EIA, 2013). A substantial uncertainty on the magnitude of lighting electricity consumption in the residential sector remains. Figure 4.1 below shows the estimates for national residential lighting consumption in 2010 from several studies.

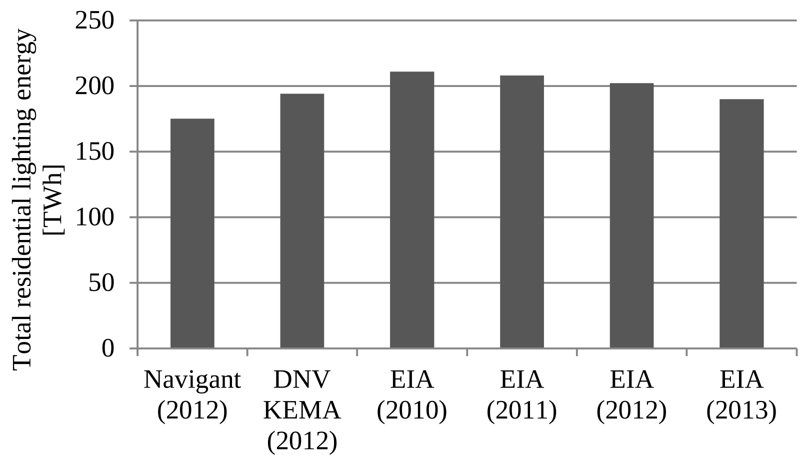


Figure 4.1 Comparison of estimates for total residential lighting electricity consumption in 2010.

In this study, we use a unique dataset of sales data from 2004 and 2009, and highlight key regional trends. This period witnessed two important events for energy-efficient lighting. First, the Energy Independence and Security Act (EISA) was enacted in 2007 setting standards on luminous efficacy of light bulbs. The EISA of 2007 defines that general service lamps have medium screw bases and light outputs between 310 and 2600 lumens (H.R. 6-110th Congress, 2007). These light bulbs are the focus of our analysis. The EISA standards were established as follows. General service lamps should satisfy the requirement shown in Table 4.1 if they are produced after the effective dates in the last column. For example, EISA contemplates that starting from January 1, 2012, all light bulbs manufactured with a rated lumen range between 1490 and 2600 should not exceed 72W and have to have rated lifetimes longer than 1000 hours. Most CFLs and LEDs that are currently being sold already satisfy the requirements.

Table 4.1 Requirements of EISA 2007 for general service lamps (H.R. 6-110th Congress, 2007)

Rated Lumen Ranges	Typical Current Lamp Wattage	Maximum Rate Wattage	Minimum Rated Lifetime	Effective Date
1490-2600	100	72	1,000 hrs	1/1/2012
1050-1489	75	53	1,000 hrs	1/1/2013
750-1049	60	43	1,000 hrs	1/1/2014
310-749	40	29	1,000 hrs	1/1/2014

Second, also in 2007, a key retailer Wal-Mart ran a nationwide campaign of selling 100 million compact fluorescent lamps (CFL) by the end of 2007. Wal-Mart announced the plan at the end of November 2006 (Wal-Mart, 2006) and achieved the goal three months early at the end of September 2007 (Wal-Mart, 2007). Within that year, they sold 162 million CFLs (D&R International, 2010). To realize the goal, Wal-Mart pursued several strategies, such as installing interactive displays in select stores starting from Jan 2007, increased shelf space for CFLs, released educational materials (e.g. online savings calculator, saving tips through Wal-Mart TV and radio, staff education through internal newsletter) (Wal-Mart, 2006), and also launched store-branded CFLs at lower prices than other brand products (Wal-Mart, 2007). It is not known whether they stopped all the promotion efforts after they achieved the goal, but they at least did not actively promote CFLs afterward (D&R International, 2010).

Besides these events, states also started residential energy efficiency programs between 2004 and 2009 offering rebates, grants, or tax benefits for energy efficient lighting products or projects. Those programs are summarized in Table 4.2. There are many other states with similar programs, but they are not included because the starting dates are not within the period or not available.

Table 4.2 Summary of state-level residential energy efficiency programs related to lighting during the period between 2004 and 2009 (U.S. Department of Energy, 2012)

State	Start date	Applicable to	Title	Benefit
Connecticut	6/1/2006	All residential	Sales and Use Tax Exemption for Energy-Efficient Products	100% exemption for residential weatherization products including CFLs
California	1/1/2006-12/31/2008	All residential	Upstream Lighting Program	Utility rebates for CFL/LED bulbs, fixtures directly to manufacturer, distributor, and retailer, resulting in an average discount for consumers at the register of $2.70 per bulb
Georgia	7/1/2008	Multi-Family Residential	Clean Energy Tax Credit	$0.60 tax credit/ft^2 of building for lighting retrofit projects
Illinois	5/19/2006	Low-Income Residential	Efficient Living Construction Grant	Grant varies based on housing type and size. Construction must meet local energy efficiency standards.
Kentucky	1/1/2009	All residential	Energy Efficiency Tax Credits	Personal tax credit of 30% of installed cost
Pennsylvania	5/1/2009	Multi-Family Residential	Alternative and Clean Energy Program	State support for alternative energy and clean energy projects in the form of loans, grants and loan guarantees. Grant Varies by project.
Texas	9/1/2009	All residential	CoServ Electric Cooperative - Residential Energy Efficiency Rebate Program	Utility rebate up to $50 for CFLs and $1.75 per LED bulb
Virginia	3/23/2007	All residential	Sales Tax Exemption for Energy-Efficient Products	100% exemption from state sales and use tax on Energy Star products

4.2. Methods and data

We use a unique dataset acquired from a marketing firm, A.C. Nielsen, via the James M. Kilts Center for Marketing, at the University of Chicago Booth School of Business (Nielsen, 2012). The dataset contains six years of purchase data of household products with Universal Product Codes (UPC) from a nationally and regionally representative panel dataset that includes about 100,000 households, which have scanned their purchases from 2004 to 2009. Participants are recruited as follows. Nielsen contacts prospective households by sending letters by mail and emails. Contacted households are randomly selected among those who match targeted demographic characteristics and represent each of strata based on nine demographic variables to both nationally and regionally represent U.S. households. The information sent out to potential participants includes a program overview and a preliminary survey. The panel membership is given to those who return the complete survey. The strata are set based on nine key demographic variables and sixty-one geographic areas (see the appendix for more detail).

Households are tasked with scanning all their purchases. The data are collected with barcode scanners distributed to panel households, who agreed to scan the Universal Product Code (UPC) on each packages of their purchase from each shopping trip. The UPC is the bar code included in purchased products. A panel household returning from a shopping trip enters information about the overall trip including shopping date and store type. If the store provides Nielsen with point-of-sale data, Nielsen imputes the price data, and if it does not, this information is entered by the participant. Households also enter the number of units purchased, whether there was a deal or promotion associated with the product, and the type of the deal (if available).

Nielsen offers various non-biasing incentives to help samples remain active in the panel, which include sweepstakes, gift points, and monthly prize drawings. Member households are removed from the program if they are not active or do not meet the minimum required spending per four-week period. On average, the dataset's panel retention rate is about 80%, which means that 80% of panel households of a year remain in the panel the next year. The annual number of scanned UPCs per household stays around one thousand for each year during the six-year period.

The number of households in the original data is around 40,000 for years between 2004 to 2006, and increases to over 60,000 per year after 2007. From 2004 to 2009 roughly 101,000 unique households are observed in the dataset. To deal with this panel imbalance, the Nielsen dataset provides a weighting factor for each household and for each year. A weighting factor value is the population within a stratum divided by the number of samples collected within the stratum. Hence, it means the number of households that a participant represents if one is to have a nationally or regionally representative sample. The mean and median of the weighting factors in our data are 2,268 and 1,065. The distribution is highly skewed to the right with the minimum of 118 and the maximum of 31,860.

We use the weighting factors to estimate light bulb sales at the country or region level. Following the categorization used by Nielsen, the four regions we use in this analysis are named as East, West, Central, and South instead of Northeast, West, Midwest, and South. These regions, shown in Figure 4.2, do not include Alaska and Hawaii.

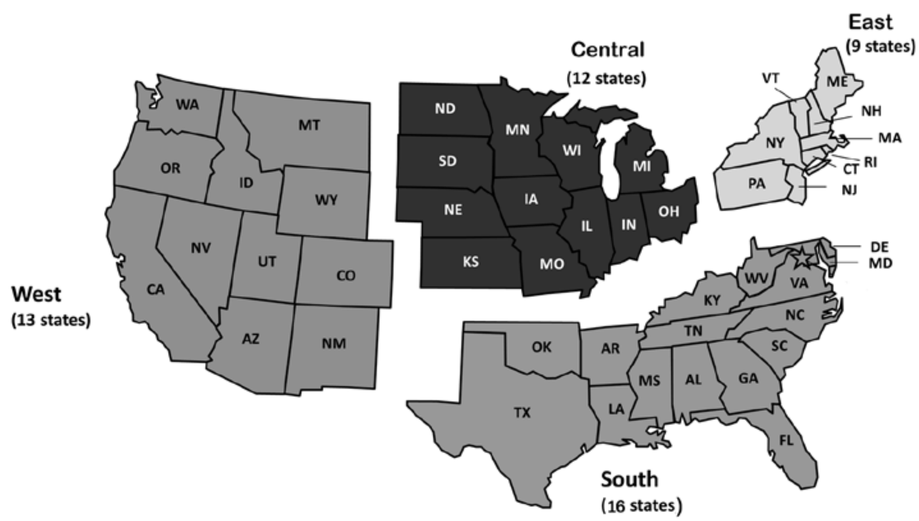


Figure 4.2 Four regions used in this analysis (U.S. Census Bureau, 2010)

The dataset shows a list of products that are purchased in each trip. For each purchased item, the following details are given: UPC number, product description, product category, brand, purchased quantity, package size, original price, existence of deals, coupon value (if available), retail channel types where items were bought. When a purchased item was on a deal, the type of the deal is coded with four levels: ‘special display’, ‘store coupon’, ‘manufacturer coupon’, and ‘other’.

The demographic information included in the dataset includes household income, household size, age and number of children, type of residence, and house zip code. The data also includes information on age, education, employment status, and occupation for the person listed as the head of the household. Figure 4.3 juxtaposes nationwide distributions of three main demographic variables from census data and the panel data used for our analysis. It should be mentioned that these panel data are for the households who have bought light bulbs and do not necessarily represent the whole population. For this reason, the panel data may under-represent renter population, which is potentially why the panel data under-represent young households as shown in Figure 4.3c. For the census data in the plots, we use the 5-year estimates for 2005 to 2009. The values used for these plots and other demographic variables are provided in Table 4.6 in the appendix. Overall, by comparing the Nielsen dataset and the census demographic information, we find that the Nielsen data provides a good representation of U.S. demographics.

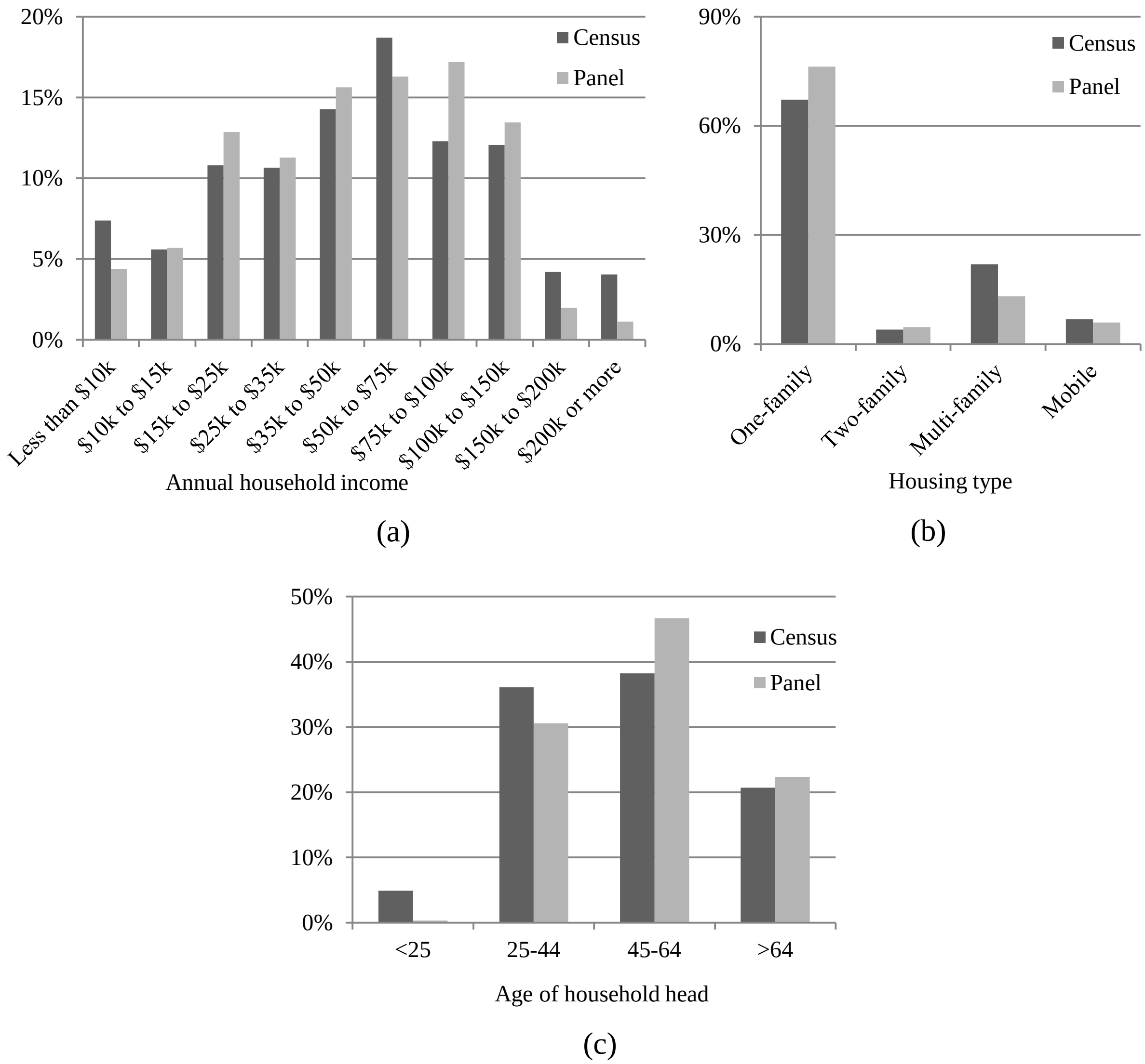


Figure 4.3 Comparison of distributions of demographic variables from Census and Nielsen's panel data. a) Annual household income; b) Housing type; c) Age of household head. The distributions for panel data are for weighted panel.

Figure 4.4 shows distributions of annual household spending on light bulbs. These histograms are only for households who bought light bulbs in each year. Those households who do not spend any money on bulbs in a given year are not shown in these histograms because having them creates high peaks at $0 and make the plots less interpretable. Percentages among total households without any lamp purchase records are 40%, 40%, 43%, 44%, 50%, and 58% for respective year between 2004 and 2009, which suggests that there are fewer consumers buying light bulbs over time.

The distributions in Figure 4.4 have very long and thin tails suggesting there are a small number of big bulb buyers for unidentifiable reasons, but still an average household spends around $10 or less on lamps each year.[23] Dotted vertical lines indicate average spending each year. More detailed values about the yearly distributions are provided in Table 4.9 in the appendix. While Consumer Expenditure Survey does not have detailed spending categories separately showing lighting products, it exhibits much larger numbers for two relevant categories of miscellaneous housewares (>$90/year) or household equipment (>$600/year) between 2006 and 2009 (U.S. Department of Labor, 2012). We observe that the mean spending per household peaks in 2007, when the highest CFL sale was recorded as shown in Figure 4.6 below.

[23] One of the potential reasons for large bulb purchases can be moving into a new house and replacing all the bulbs. But while there are a few households that can match the hypothesis, but we observe more commonly that households who spent over $150 in a year on light bulbs either have lived in the same zip code area for multiple years or have been purchasing bulbs over many shopping trips throughout a year, which may not directly support the reason.

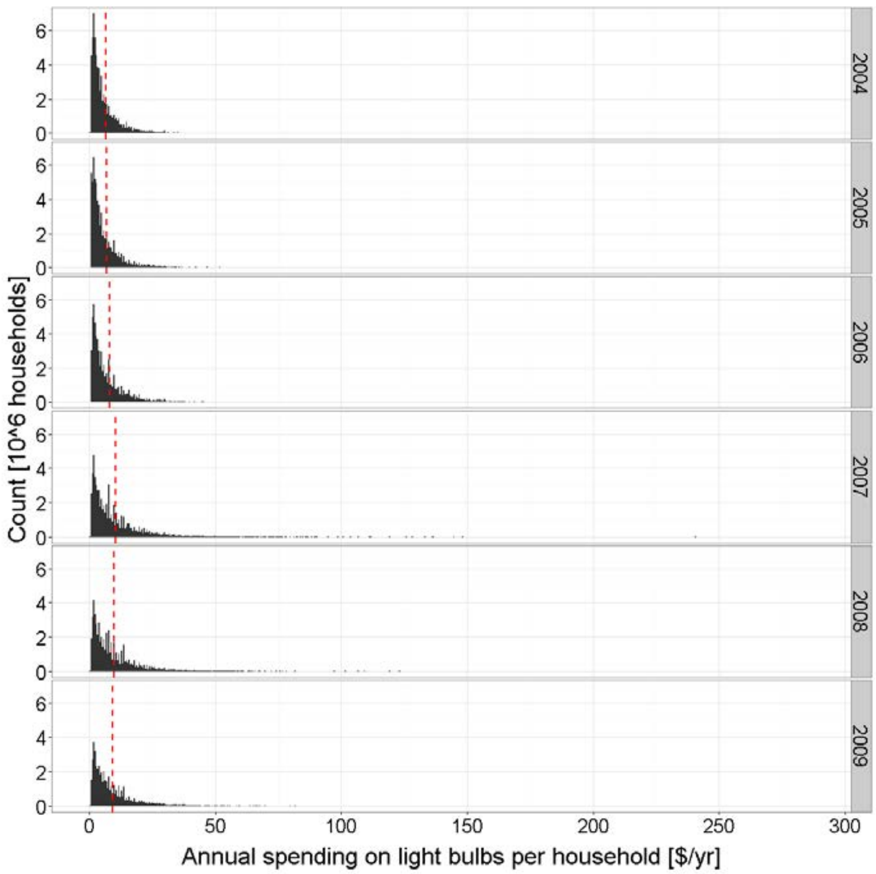


Figure 4.4 Histograms of annual average spending on light bulbs per household. The red dotted vertical lines show the location of means each year. These histograms are only for those households who have bought light bulbs in each year. Percentages of these households among all observations are 60%, 60%, 57%, 56%, 50%, and 42% for respective year between 2004 and 2009.

Information on retail channels: The original dataset includes 65 mutually exclusive retail channel types. From these, there are 63 retail channel types where light bulbs were sold. These are listed in the appendix, Section A4.2. The six major channels of light bulbs purchases are discount stores, drug stores, hardware stores, groceries, warehouse clubs, and dollar stores, accounting for more than 96% of light bulb sales in any year. Under each channel type (e.g. hardware store), there are several retail chains. Each of these retail chains (e.g. Home Depot) has a retailer ID code. However, there is no information in the panel data matching each retailer ID code to a specific retail chain. For about a third of purchase observations, store IDs are also available which differentiate individual stores under a chain.

Information on light bulbs: According to Nielsen's taxonomy, light bulbs belong to a product group of "Light Bulbs, Electric Goods" under a product department of "General Merchandise". The product group includes two product modules: "Lamps - Incandescent" and "Lamps - Remaining". The product description field has short encoded texts (e.g. 'PH L-L S-W 100W' indicating a 100W long-life soft white bulb from Philips) providing limited information about the product. The encoding scheme is not included in the dataset, and types of information given in the field are not always consistent. For example, some fields show the bulb shape information (e.g. A19) while others do not. The original panel data did not provide any information about technical characteristics of a product. For light bulbs, for example, only the wattage information could be easily inferred from the product description field. We complemented the original dataset by matching the UPC codes with technical information scraped from online stores. This lead to matching about 8% of all UPCs under the "Light Bulbs, Electric Goods", corresponding to about 29% of total light bulbs sales in any given year. For most bulbs in that subset, we were able to complement the original dataset with additional information from the product description field, namely lumen, life, dimension (length and width), color, shape, and base type. When no information was provided about the bulb/socket shape, we assumed the product was an intermediate base and A-shape, which are the most common attributes in the market.

Combined dataset: We selected purchases corresponding to general service light bulbs. Among those bulbs satisfying these criteria, to observe preferences for bulbs with similar use purpose, only the A-shape bulbs are considered. Brands that have less than 1% of total sales share were excluded. Also, bulb purchases that are not from the six major channels are removed. For example, less than 4% of total observations are from unlikely store types (e.g. coffee store or bakery). Only CFLs and incandescent bulb purchases are analyzed. Light-emitting diode (LED) bulb purchases are not considered because all purchase observations which can be categorized as LEDs are night lights or other non-general service lamps (e.g. too dim or different base types). Some original observations under the product group "Light Bulbs, Electric Goods" are removed based on brand names, when those brands are dedicated to other types of lighting products (e.g. locomotive lights, lighting fixtures, etc.) that are not general service light bulbs. This data selection process leads to a final set of 2,490 bulb products (differentiated by unique UPCs). From 2004 to 2009, about 75,000 distinct households purchased about 352,000 general service light bulb items. The final dataset contains four alternative-specific attributes of light bulbs: price, wattage, type, and package size. The price, type and package values are originally reported through dedicated fields in the Nielsen data, while wattage values had to be constructed based on the product description field provided by Nielsen.

4.3. Analysis

Market characterization by retail type: Figure 4.5a shows the sales by UPC from 2004 to 2009. The plot shows the top 100 bestselling items among the 2,490 UPCs. These 100 bulbs account for about 60% of all sales from 2004 to 2009. More detailed information on top five bestselling products for each type is given in Table 4.3 and 4.4 below.

Figure 4.5b shows sales from top 50 retailer chains in terms of number of light bulbs sold. There are total 640 distinct retail chains identified by the retailer ID field in the data. The top 50 retailers shown in Figure 4.5b sold 87% of all general service light bulbs. Just the top five retailers account for 43% of sales. We note that the top selling retailer chain is a discount store that is selling about three times the sales of the second retailer, which is also a discount store. Examples of discount stores are Wal-Mart, Target, and Kmart. Table 4.5c and 4.5d are separately for incandescent lamps and CFL sales. The 1st place retailer chains in Figure 4.5b, 4.5c, and 4.5d have an identical retailer ID. Although the Nielsen data reveal only the codified IDs of retailers, we can speculate who the most dominant retailer is from other available information. From an online UPC search service provided by international standards organizations such as GS1 (GS1, 2014), we find that many among the bestselling UPC values from the top seller are the ones assigned to Wal-Mart.[24] From this, we infer the top bulb seller is Wal-Mart. We see that light bulb sales are highly concentrated to a few large retailer chains headed by Wal-Mart.

[24] However, this method does not work for other retailers who do not have custom brand items.

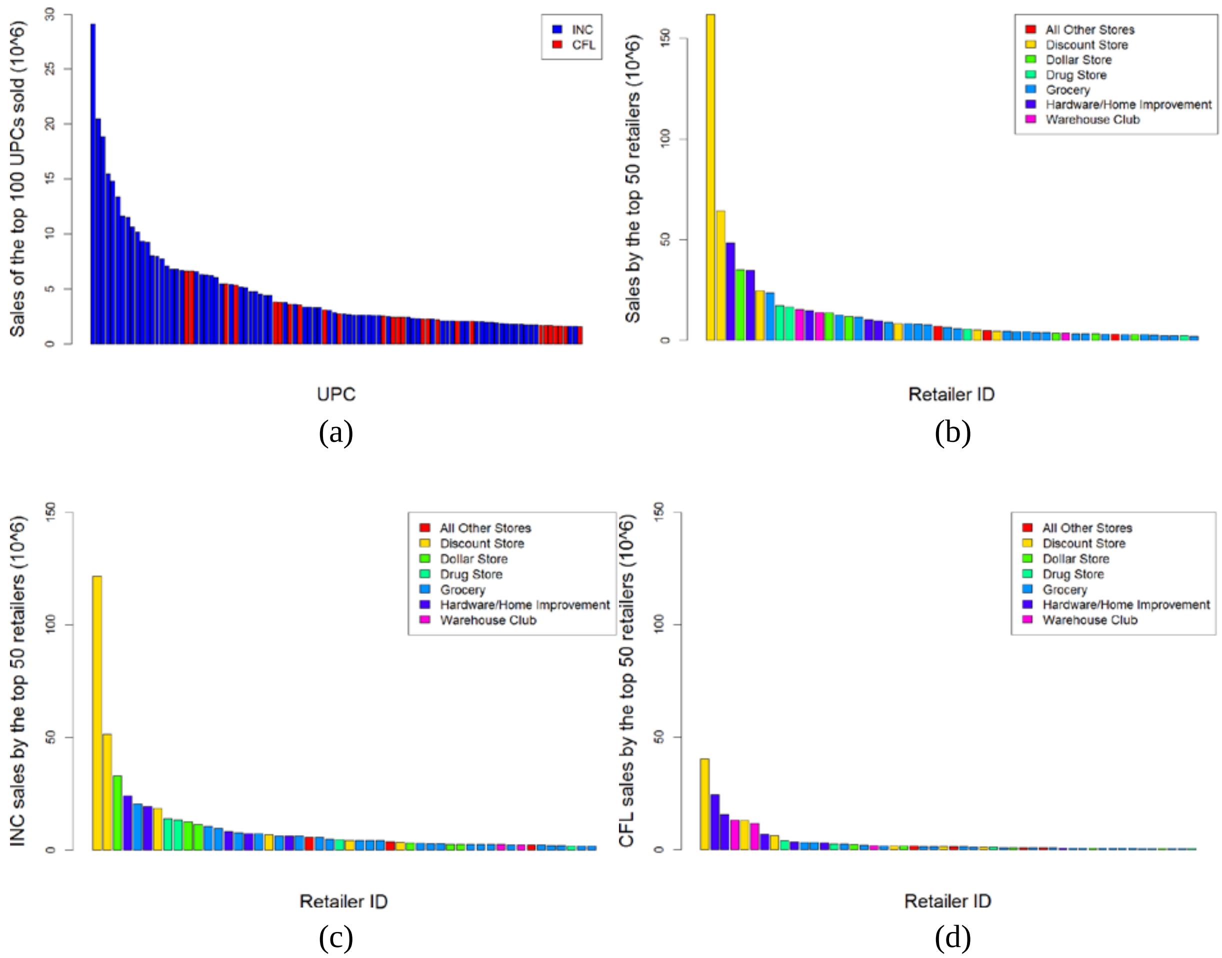


Figure 4.5 (a) Histogram of light bulb package sales by product code (UPC) for the top 100 selling bulb products from 2004 to 2009. UPC codes corresponding to incandescent lamps are showed in blue, and compact fluorescent lamps UPC codes are shown in red; b) Histogram of light package bulb sales by for the 50 retailer chains with the largest number of sales from 2004 to 2009, by retailer type; c) Similar histogram only for incandescent bulb sales by retailer type; d) Histogram only for CFL sales by retailer type.

Table 4.3 and 4.4 presenting the five bestselling UPCs for each type show that GE is the dominant manufacturer in light bulb market. The most popular power level for incandescent bulbs is 60W, which normally produces around 840 lumens, and is equivalent to a 13W CFL. The bestselling incandescent bulbs are all sold in four-bulb packages, but CFLs are sold in various package sizes. Whether bulbs are on any types of deals is not a necessary condition determining the popularity, especially when the unit price is low. The top 5 incandescent light bulbs in Table 4.3 represent more than 12% of total general service light bulb package sales from 2004 to 2009. Similarly, the top 5 CFLs in Table 4.4 represent about 3.5% of total light bulb package sales during the same period.

Table 4.3 The five most popular UPCs for incandescent lamp packages from 2004 to 2009. All of the top five incandescent bulbs were 60W and sold in packages of 4. The column "%Deal" represents percentage of all sales that were on any types of deals.

Incandescent Light bulbs							
Brand	Avg. price ($/bulb)	Life (hour)	Brightness (lumen)	Color (K)	% Deal	Sales (million pkg)	% of total light bulb package sales
GE	0.29	1000	840	2800	16%	29	3.6%
GE	0.38	1000	840	2800	52%	21	2.6%
GE	0.68	1000	630	2800	36%	19	2.4%
Wal-Mart Great Value	0.20	N/A	N/A	N/A	3%	16	1.9%
Wal-Mart Great Value	0.20	N/A	N/A	N/A	5%	15	1.9%

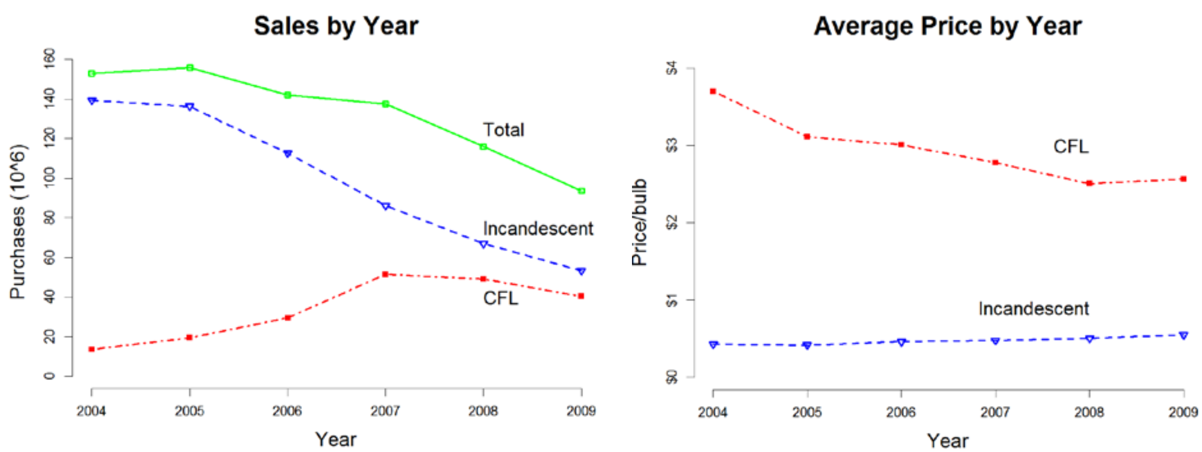
Table 4.4 The five most popular UPCs for CFL lamp packages from 2004 to 2009. All of the top five CFLs were GE products. The column "%Deal" represents percentage of all sales that were on any types of deal.

CFLs									
Brand	Watt	#/pkg	Avg. price ($/bulb)	Life (hour)	Brightness (lumen)	Color (K)	% Deal	Sales (million pkg)	% of total light bulb package sales
GE	13	8	1.49	8000	825	2700	2%	6.6	0.8%
GE	13	3	2.48	8000	825	2700	13%	6.6	0.8%
GE	26	3	2.55	10000	1750	2700	13%	5.4	0.7%
GE	26	1	4.14	10000	1750	2700	53%	5.4	0.7%
GE	15	1	3.24	8000	950	2700	54%	3.8	0.5%

Figure 4.6 shows trends of light bulb purchases and price per bulb appearing in the data. The total light bulb sales decrease over time while CFL sales peaked in 2007 and deceased afterward. Potential reasons for the peak can be either the enactment of the Energy Independence and

Security Act (EISA) or the nationwide CFL campaign by Wal-Mart in 2007 as explained in the introduction. The total sales decrease can be due to the longer lifetime and turnover rate of CFLs or the economic plunge starting from 2008.

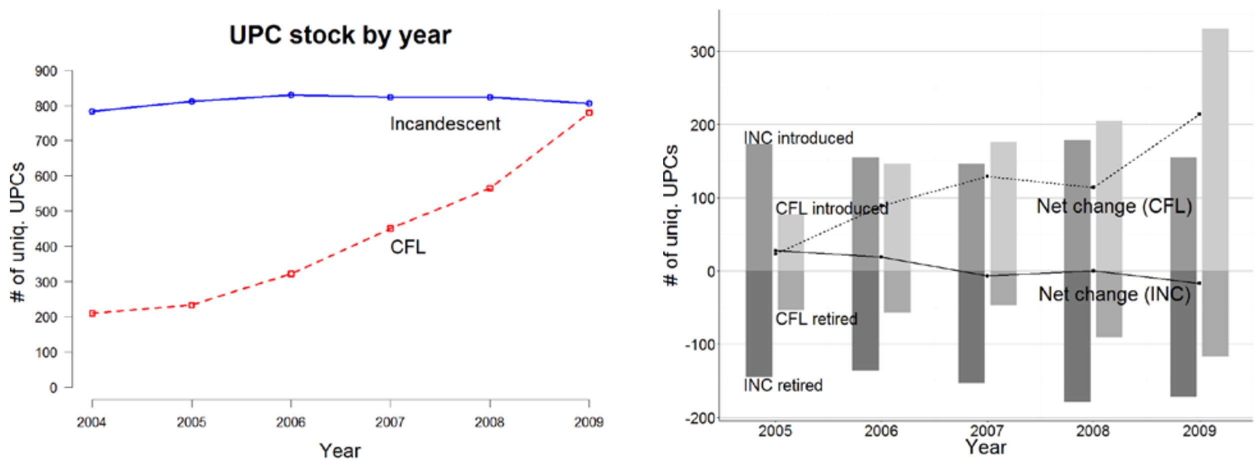
While average price for an incandescent bulb kept increasing slowly ($0.43 in 2004 to $0.59 in 2009), CFL price almost monotonically decreased to the lowest ($2.57) in 2008 but slightly increased to $2.72 in 2009.



(a) (b)

Figure 4.6 (a) Quantity of incandescent lamps and CFLs sold each year, scaled by weighting factors to provide a nationally representative sample; (b) Weighted average prices for incandescent lamps and CFLs from 2004 to 2009.

The peak in CFL sales in year 2007 could be driven by either change of consumer preferences or change in product availability because manufacturers react to the new regulation or other changes in the business environment. Figure 4.7a shows the number of unique UPC items each year for the two technologies. The number of CFL items increased over the six years, while the number of incandescent items stayed almost at a constant level. Figure 4.7b is for the changes in the stock for each type. The bar graph displays the number of the new or retired UPCs in each year for each type. We see that the number of newly introduced CFLs rapidly increased especially in 2009. This observation suggests that manufacturers emphasized new efficient lamp products. We also assessed the total number of unique producer codes, which is identifiable from the first six digits of UPC, and found that the number of CFL manufacturers notably increased after 2007. There have been around 20 brands or companies manufacturing CFLs until 2007 but the number increases to 35, 46, and 58 in 2007, 2008, and 2009 respectively.

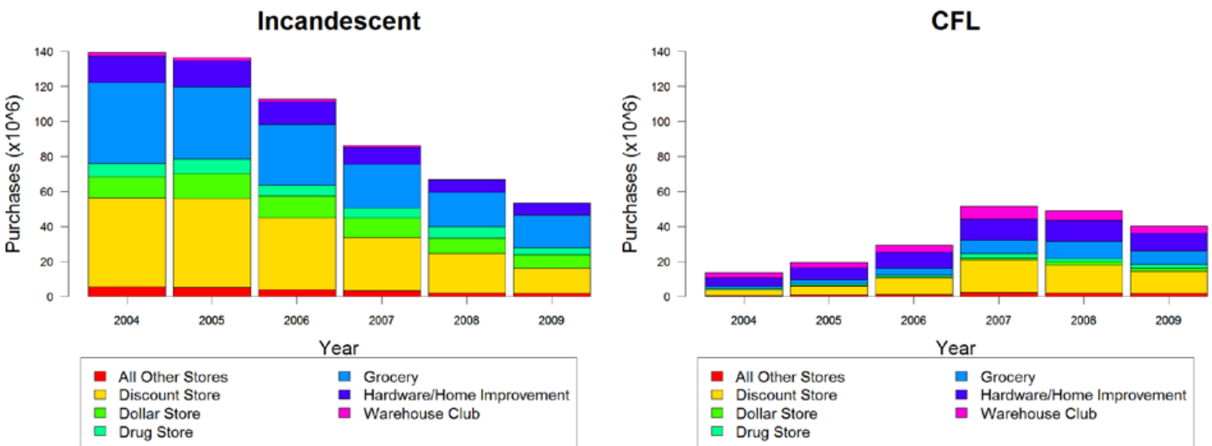


(a) (b)

Figure 4.7 Sales and price trends of each light bulb type during 2004-2009. a) Total number of unique UPCs per year; b) Number of unique UPCs introduced and retired each year. The bar graphs are for the total number of introduced or retired UPCs each year. The lines show net changes in number of unique UPCs.

There are 640 distinct retailer chains that sold light bulbs between 2004 and 2009. The sales distribution across store types is shown in Figure 4.8. The sales values are weighted by the weighting factor. The distributions are very distinct between CFLs and incandescent bulbs. Incandescent bulbs are bought predominantly at discount stores and grocery stores, while a majority of CFLs are bought in hardware stores or discount stores. Also, warehouse clubs play a very important role in CFL sales while nearly negligible for incandescent bulb sales.

The numbers of distinct chains under each retailer type are shown in Table 4.5. We see that while grocery chains are the largest seller of incandescent bulbs in total according to Figure 4.8a, sales from each grocery chain will be small when divided by the large number of grocery chains in the data. On the other hand, average sales per discount or hardware store chain will be large since there are not many distinct chains.



(a) (b)

Figure 4.8 Breakdowns of light bulb sales by store types. a) Incandescent bulbs; b) CFLs.

Table 4.5 Number of distinct retail chains that sold light bulbs between 2004 and 2009.

Type	Discount Store	Dollar Store	Drug Store	Grocery	Hardware Store	Warehouse Club	Other	Total
Number	15	13	29	380	12	6	185	640

Figure 4.9 shows the number of unique UPC items purchased in each store type each year across the country. Because this is for each retailer type, the same UPC can be counted in more than one retailer types. While grocery stores appear to have the widest variety of incandescent bulbs, again it is probably because there are many more grocery stores than hardware or discount stores, as shown in Table 4.5. Consistently with Figure 4.7, counts of incandescent bulb UPCs at each

store type did not decrease significantly over time, while counts of CFL UPCs constantly increase. This suggests that the manufacturers are not phasing out incandescent bulbs ahead of the EISA of 2007 taking effect in years to come.

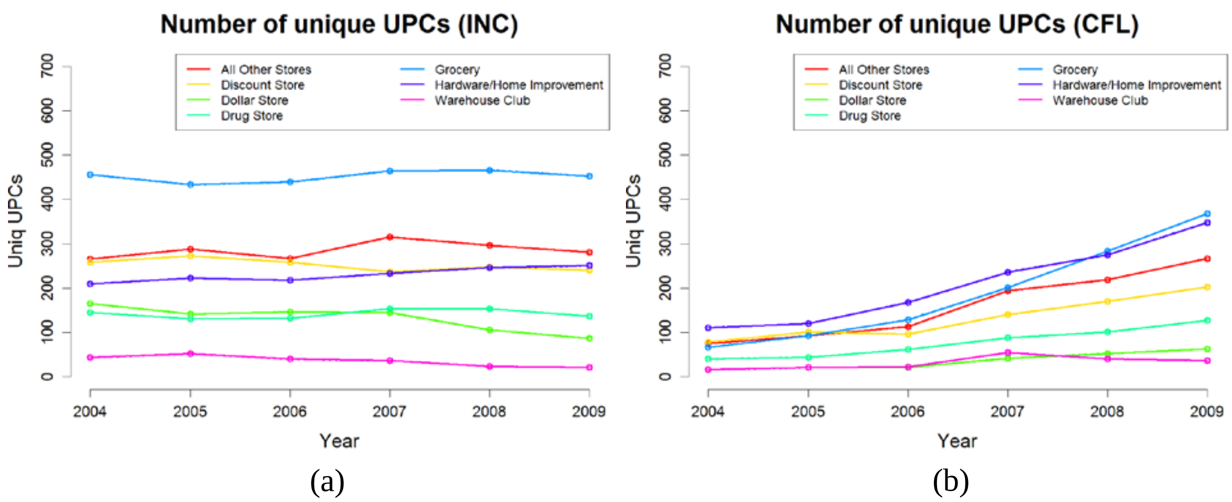


Figure 4.9 Number of unique UPCs sold at each store type. a) Incandescent bulbs; b) CFLs

The proportion of efficient light bulb sales among total general service light bulb sales also varies across store types and years. Figure 4.10 shows that a majority of bulb sales from warehouse stores are CFLs, while in dollar stores, the ratio is as low as 20% in 2008 or 2009. The ratio generally increases over time except for the year 2009, in which year groceries, hardware stores and dollar stores recorded lower CFL purchase rates than in 2008. The slope of the curves was the steepest between 2006 and 2007, which corresponds with the CFL sales trend shown in Figure 4.8b. Considering that groceries and hardware stores are the main sellers of CFLs, the downward slopes of the two corresponding curves in Figure 4.10 explain the drop in overall CFL sales in 2009. Based on the finding, we can at least say that the drop in 2009 is not mainly because of the discontinued promotion efforts in discount stores.

Across the six retail channel types, there are vast differences in purchase patterns. Sales data shows consumers generally buy more efficient bulbs from hardware stores and warehouse clubs, while in drug stores, dollar stores, discount stores, and grocery stores, consumers choose more inefficient lamps. This can possibly be because of a difference in availability of efficient light bulbs across channel types, but demographic attributes and their relationship to store choices are likely to play an important role as well.

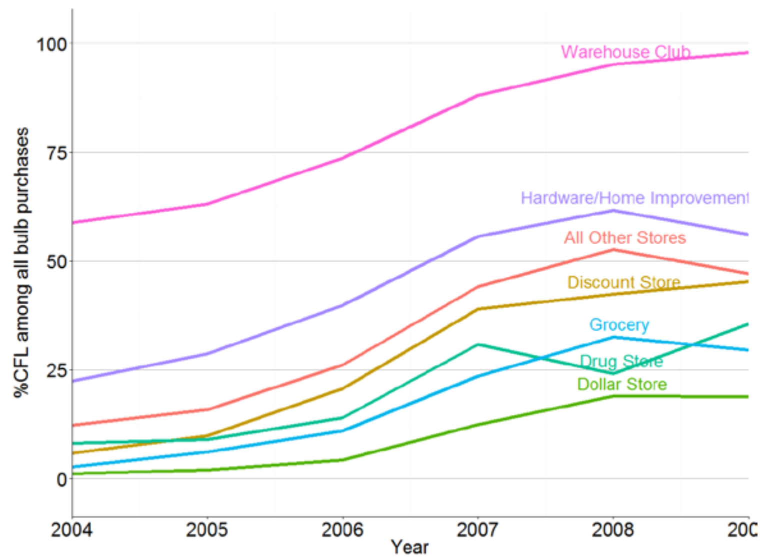


Figure 4.10 Trends of percentage of CFLs among all general service bulb purchases from each store type.

Representative region-level trends are shown in Figure 4.11. Each of the eight different areas is for each combination of region and type. The top four areas in lighter colors are for CFLs and the lower four in darker colors are for incandescent lamps. Figure 4.11a shows that CFLs sales increased while incandescent lamp sales decreased. Total lamps sales are highest in South region mainly because of its largest population. Figure 4.11b and 4.11c represent annual electricity consumption and carbon emission from the bulbs purchased within each year. To calculate the electricity consumption, we adopt daily hours of use (HOU) per each type of bulbs in each region from DNV KEMA (2012). According to the report, daily HOU of incandescent lamps is normally between 1.2 and 1.3 hours/day, while that of CFLs is between 1.8 and 2.0 hours/day. In Table 4.10 in the appendix, we show these assumptions by region. Regional emission factors for each year are based on state-level emission factors adopted from eGRID (U.S. EPA, 2012). But since eGRID does not have emission factors for every year, we used the previous year's values for the year for which eGRID data are not available. CO_2 emission factors have decreased over time in all regions. Figure 4.11d shows lumen-hours produced each year from the new lamps.

Figure 4.11 shows that total sales gradually decrease over the period in all regions as we also observed above. The magnitude of decrease is largest in South region, where the most CFLs were sold over the years. While CFLs consume much less electricity and emit less CO_2 than incandescent lamps (Figure 4.11b and 4.11c), they generate even more lumen-hours after 2007 according to Figure 4.11d. Due to increasing adoption of CFLs, newly purchased light bulbs contribute to lowering carbon emissions and electricity consumption during the period, while not sacrificing lumen-hours as much.

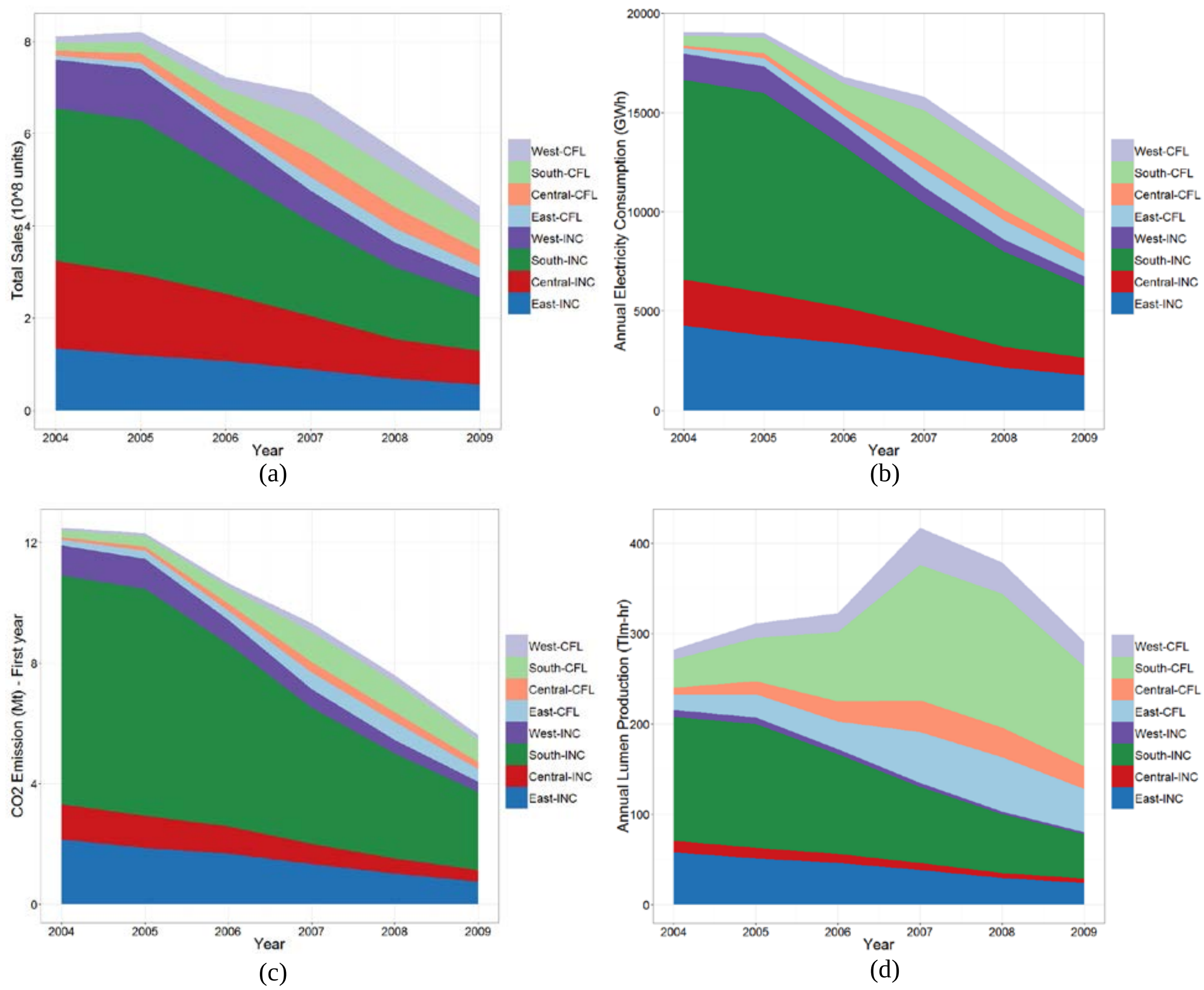


Figure 4.11 Light bulb sales, electricity consumption, lumen production, carbon emission by type, region and year. a) Total sales; b) annual electricity consumption; c) annual CO_2 emission ; d) annual lumen production. Areas with lighter colors are for CFLs, while darker areas are for incandescent bulbs. Similar colors identify different regions.

4.4. Conclusion and policy implications

We investigated trends of light bulb sales from an extensive consumer panel dataset spanning from 2004 to 2009. We focused on general service incandescent lamps and CFLs as defined in the EISA of 2007.

Total light bulb sales are observed to decrease almost monotonically over the period, while CFL sales increased until 2007 and then went down for two straight years afterward. The peak of CFL sales in 2007 is probably because of the enactment of the EISA of 2007 or the aggressive campaign by a key retailer in the same year.

Within the period, new CFL products represented by unique UPCs are constantly introduced to the market increasing from about 200 items in 2004 to 800 items in 2009, while the number of distinct UPCs of incandescent lamps stays constant at around 800 during the period. We can conjecture that manufacturers are trying to adapt to the new market environment caused by the EISA of 2007. Even with the continuing variety of incandescent bulbs, constantly shrinking sales of incandescent lamps show that the market is transforming.

Light bulb sales are heavily concentrated to several key retailers, which can imply that efforts taken by these retailers can influence nationwide adoption of efficient lighting. Discount stores are where the most consumers go to buy light bulbs, while grocery store is the second largest seller of incandescent bulbs, and hardware store is the second for CFL sales. Across all retailer types we observed, CFL adoption was increasing almost consistently until 2008, while it slightly drops in hardware stores and groceries in 2009.

CFL adoption rates vary by state and region, which means that the preferences are driven by combinations of certain geographically varying factors. These factors can be policies, demographics, electricity rate structures, etc. Further studies are needed to figure out which factors are influential to the regional (or state-level) differences in adoption rate.

Appendix

A4.1. Demographic variables used to recruit the sample from Nielsen data.

According to Nielsen's data manual, the nine demographic variables used for the recruitment of samples are:

- Household Size (4 levels)
- Household Income (4 levels)
- Household Head Age (4 levels)
- Female Head Education (4 levels)
- Male Head Education (4 levels)
- Race (3 levels)
- Hispanic (Y/N)
- Household Head Occupation (3 levels)
- Presence of Children <18 (Yes/No)

Table 4.6 presents a summary of key demographic variables.

Table 4.6 Summary of demographic variables. Values in the table are for weighted samples. The number of original samples is N=351,712. Plots comparing the national percentage values are provided in Figure 4.3.

Region		Census National	Census East	Census Central	Census South	Census West	Nielsen National	Nielsen East	Nielsen Central	Nielsen South	Nielsen West
Number of households		113M	21M	26M	42M	25M	62M	11M	15M	25M	12M
Average household size		2.61	2.57	2.50	2.59	2.77	2.62	2.61	2.57	2.58	2.78
Housing type	One-family	67.3%	60.3%	72.4%	67.8%	66.7%	76.3%	65.5%	80.7%	79.4%	74.6%
	Two-family	3.9%	8.7%	4.2%	2.3%	2.4%	4.6%	10.0%	4.4%	2.6%	4.0%
	Multi-family	21.9%	28.2%	18.7%	19.5%	24.5%	13.2%	21.8%	11.2%	9.6%	14.8%
	Mobile	6.8%	2.8%	4.7%	10.4%	6.4%	5.9%	2.6%	3.8%	8.4%	6.5%
Age of household head	<25	4.9%	3.2%	5.6%	5.3%	5.0%	0.3%	0.3%	0.4%	0.3%	0.3%
	25-44	36.1%	34.6%	35.2%	36.5%	37.8%	30.6%	28.7%	30.9%	30.9%	31.4%
	45-64	38.2%	39.9%	38.1%	37.5%	38.2%	46.7%	48.3%	45.8%	46.6%	46.4%
	>64	20.7%	22.2%	21.0%	20.7%	19.1%	22.4%	22.7%	22.9%	22.2%	21.8%
Household income	Less than $10k	7.4%	7.1%	7.3%	8.5%	5.9%	4.4%	4.5%	4.1%	5.0%	3.6%
	$10k to $15k	5.6%	5.2%	5.6%	6.1%	5.1%	5.7%	5.4%	5.4%	6.4%	4.9%
	$15k to $25k	10.8%	9.7%	11.1%	11.7%	9.9%	12.9%	11.4%	12.1%	14.4%	12.1%
	$25k to $35k	10.7%	9.4%	11.1%	11.4%	10.0%	11.3%	10.2%	11.3%	12.1%	10.7%
	$35k to $50k	14.3%	12.8%	15.0%	14.8%	13.9%	15.6%	13.9%	16.4%	15.9%	15.8%
	$50k to $75k	18.7%	18.0%	19.8%	18.3%	18.8%	16.3%	15.9%	17.3%	15.9%	16.2%
	$75k to $100k	12.3%	12.9%	12.7%	11.4%	12.9%	17.2%	18.3%	18.0%	15.9%	17.9%
	$100k to $150k	12.1%	14.0%	11.2%	10.7%	13.7%	13.5%	15.8%	13.0%	11.9%	15.0%
	$150k to $200k	4.2%	5.4%	3.4%	3.6%	5.1%	2.0%	2.9%	1.7%	1.7%	2.2%
	$200k or more	4.1%	5.6%	2.9%	3.5%	4.9%	1.1%	1.7%	0.8%	0.8%	1.8%

A4.2. Retail channel types where light bulbs were sold and number of light bulbs sold by year

The original data from Nielsen have 65 retailer categories, and 63 among them have sold light bulbs between 2004 and 2009. We present below the top and the bottom 20 retail channels and corresponding sales by year weighted by the projection factor. The table is ordered by sales in 2004. Looking at the table for bottom 20 (Table 4.8) suggests that input errors by panelists do exist in the dataset. There are many unlikely retailer types which are recorded as selling light bulbs such as fish market or fruit stand. For this reason, in our analysis we only focus on the sales from the top 6 retailer types, which take about 96% of total sales every year.

Table 4.7 Top 20 retail channels of light bulb sales (values in thousand units). Values in the table are weighted sales and corresponding shares in each year. Rows are ordered by the sales in 2004. Only the observations for the top six channels are used for our analysis.

Channel	2004		2005		2006		2007		2008		2009	
Discount Store	54084	35.4%	56245	36.1%	50289	35.4%	49019	35.7%	38200	33.0%	26441	28.2%
Grocery	47348	31.0%	43789	28.1%	38440	27.1%	32210	23.4%	28855	24.9%	25731	27.5%
Hardware/Home Improvement	19637	12.8%	21585	13.9%	22180	15.6%	21660	15.8%	19480	16.8%	17190	18.4%
Dollar Store	12320	8.1%	14544	9.3%	13173	9.3%	12431	9.0%	10922	9.4%	9754	10.4%
Drug Store	8124	5.3%	8867	5.7%	7255	5.1%	8384	6.1%	8745	7.5%	6443	6.9%
Warehouse Club	5352	3.5%	4899	3.1%	5657	4.0%	8325	6.1%	5695	4.9%	4430	4.7%
Military Store	1903	1.2%	1871	1.2%	1749	1.2%	1337	1.0%	1014	0.9%	786	0.8%
Close Out Store	1070	0.7%	1017	0.7%	547	0.4%	683	0.5%	228	0.2%	293	0.3%
All Other Stores	869	0.6%	857	0.6%	713	0.5%	979	0.7%	830	0.7%	776	0.8%
Department Store	537	0.4%	552	0.4%	418	0.3%	254	0.2%	182	0.2%	167	0.2%
Online Shopping	529	0.3%	517	0.3%	594	0.4%	1212	0.9%	912	0.8%	843	0.9%
Coop/Farm/Feed	200	0.1%	262	0.2%	186	0.1%	115	0.1%	127	0.1%	78	0.1%
Convenience Store	123	0.1%	86	0.1%	138	0.1%	158	0.1%	119	0.1%	61	0.1%
Office Supplies Store	123	0.1%	64	0.0%	51	0.0%	74	0.1%	89	0.1%	90	0.1%
Home Furnishings	93	0.1%	84	0.1%	129	0.1%	138	0.1%	163	0.1%	182	0.2%
Free Sample/Gift	84	0.1%	57	0.0%	62	0.0%	100	0.1%	77	0.1%	76	0.1%
Automotive Store	81	0.1%	21	0.0%	19	0.0%	14	0.0%	7	0.0%	2	0.0%
Swap Meet/Flea Market	77	0.1%	68	0.0%	79	0.1%	24	0.0%	22	0.0%	26	0.0%
Apparel Stores	45	0.0%	91	0.1%	76	0.1%	16	0.0%	10	0.0%	5	0.0%
Hypermarket	40	0.0%	19	0.0%	7	0.0%	31	0.0%	10	0.0%	15	0.0%

Table 4.8 Bottom 20 retail channels of light bulb sales (values in thousand units)**.** Values in the table are weighted sales and corresponding shares in each year. Rows are ordered by the sales in 2004. It is probable that many of these data are falsely input by the participant households.

Channel	2004		2005		2006		2007		2008		2009	
Garden Stores	1	0.0%	3	0.0%	9	0.01%	17	0.01%	5	0.0%	12	0.01%
Pet Store	1	0.0%	0	0.0%	0	0.0%	5	0.0%	1	0.0%	2	0.0%
Health Food Store	1	0.0%	12	0.01%	1	0.0%	15	0.01%	11	0.01%	1	0.0%
Fish Market	0	0.0%	2	0.0%	1	0.0%	0	0.0%	0	0.0%	0	0.0%
Computer Store	0	0.0%	11	0.01%	0	0.0%	8	0.0%	0	0.0%	0	0.0%
Liquor Store	0	0.0%	16	0.01%	6	0.0%	11	0.01%	15	0.01%	12	0.01%
Sporting Goods	0	0.0%	4	0.0%	5	0.0%	8	0.01%	2	0.0%	3	0.0%
TV/Home Shopping	0	0.0%	1	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Athletic Footwear	0	0.0%	0	0.0%	7	0.01%	1	0.0%	1	0.0%	0	0.0%
Barber/Salon	0	0.0%	0	0.0%	10	0.01%	0	0.0%	0	0.0%	0	0.0%
Beauty Supply Store	0	0.0%	0	0.0%	11	0.01%	4	0.0%	8	0.01%	4	0.0%
Fruit Stand	0	0.0%	0	0.0%	1	0.0%	0	0.0%	0	0.0%	0	0.0%
Pro Shop	0	0.0%	0	0.0%	1	0.0%	0	0.0%	0	0.0%	0	0.0%
Beverage Store	0	0.0%	0	0.0%	0	0.0%	8	0.01%	3	0.0%	0	0.0%
Candy Store	0	0.0%	0	0.0%	0	0.0%	0	0.0%	2	0.0%	0	0.0%
Coffee Store/Gourmet Coffee Shop	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Party Supply Store	0	0.0%	0	0.0%	0	0.0%	4	0.0%	0	0.0%	0	0.0%
Shoe Store	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Tobacco Store	0	0.0%	0	0.0%	0	0.0%	2	0.0%	8	0.01%	0	0.0%
Vending Machine	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%

A4.3. Supplemental tables

In Figure 4.4, we presented the distribution of annual spending on light bulbs per household for each year. Table 4.9 provides summary statistics of the distributions. Figure 4.4 does not include households who spend zero dollars on light bulbs. The percentages of these households in each year are also shown in the last column in Table 4.9.

Table 4.9 Spending on light bulbs per household with bulb purchase record (in nominal $). There are a small number of big spenders, but the mean and median spending is below or around $10/year. These values are for only the households with light bulb purchase records. There are households who do not buy light bulbs at all for entire year.

	Annual spending on light bulbs per household [$]				%households without light bulb purchase records
Year	Min	Median	Mean	Max	
2004	0.4	4.0	6.5	181.4	40%
2005	0.3	4.2	7.0	213.6	40%
2006	0.0	5.0	8.2	162.4	43%
2007	0.1	7.1	10.8	278.8	44%
2008	0.0	7.0	10.3	287.3	50%
2009	0.2	6.4	9.5	243.0	58%

The numbers in Table 4.10 are used to estimate annual electricity consumption from newly installed light bulbs in Figure 4.11b.

Table 4.10 Average daily HOU of each type of light bulb [hours/day] (DNV KEMA, 2012). These assumptions are used to estimate electricity consumption from newly-purchased light bulbs in Figure 4.11b.

	East	Central	South	West
Incandescent	1.27	1.22	1.23	1.22
CFL	1.97	1.93	1.91	1.89

5. Understanding lighting choices using real sales data

5.1. Introduction

In this chapter, we analyze consumers' lighting technology choices based on a consumer panel dataset, which is available between 2004 and 2009. This dataset was the one described in detail in Chapter 4. As explained in the previous chapter, within this period, the Energy Independence and Security Act (EISA) was enacted in 2007 setting standards on luminous efficacy of light bulbs. Also, a key retailer, Wal-Mart, ran a nationwide campaign promoting compact fluorescent lamps (CFL) in that same year. Building on this background and key findings from the previous chapter, we attempt to investigate consumer preferences by estimating choice models, from which we assess which factors or events influences adoption of an efficient lighting technology. We validate the qualitative observations from the previous chapter and estimate willingness-to-pay (WTP) for light bulb attributes. After that, we estimate the implicit discount rates (IDR) that consumers use when making lighting choices. Finally, we compare the WTP and IDR estimates from using this real sales data (i.e., revealed WTP and IDRs) with the ones computed based on the experimental study in Chapter 3.

5.2. Previous studies using consumer panel data

Consumer panel databases, mainly from either A.C. Nielsen or IRI (Information Resources, Inc.), have been widely used for marketing research studies. The first question all of these studies try to answer is *what* will be bought and *who* is going to buy (Guadagni and Little, 1983; Elrod, 1988; Kamakura and Russell, 1993). In addition, studies focus on *how consumers behave* (or *appear to behave*) when making purchase decisions (Hardie et al., 1993; Siddarth et al., 1995; Erdem, 1996; Chiang et al., 1998; Bell and Lattin, 2000; Bronnenberg et al., 2010). The former group of studies usually estimates implicit brand values, study the impacts of marketing efforts or other attributes, or try to understand how alternatives in a category fare against each other in the market. The second group of studies focuses on building models that can emulate consumers' specific behavioral patterns and comparing those models with other simpler models not considering the patterns. However, it should be noted that even when those new models outperform simpler models, it does not mean that consumers behave following the modeled mechanism, but instead that the model is better at explaining (or predicting) observed choices. We will provide reviews of some representative studies from each group.

Studies on what will be bought and who is going to buy

Guadagni and Little (1983) provide a seminal study using multinomial logit (MNL) choice models to consumer market research using panel data. The authors adopt a typical form of linear utility MNL model including brand, regular price, promotion dummy, promotional price cut, information on previous purchases, and brand- or size-loyalty measure they devised. The main goal was to find out consumer responses to different marketing-mix variables for customers with varying levels of brand loyalty.

Studies including Elrod (1988) and Kamakura and Russell (1993) attempted to quantify importance of intangible attributes of closely competing brands and how it relates to other attributes. Elrod assumes these mature products, through close competition, are different only in intangible attributes (i.e., attributes that are not explicitly measured). From these efforts, marketing managers can understand where their products and other competitors are positioned in the market.

Our models that will be explained below start with a similar modeling method to these studies. Unlike these studies which could obtain retailer data about what items were available in stores when customers purchased certain products, we do not have the information.[25] Moreover, the authors managed to keep the size of choice sets small by focusing on simple products with a small number of attributes (e.g. powder detergent, basic ground coffee) or sometimes fixing certain attributes such as package size or limiting to specific geographic region. In this study, we attempt to estimate models including all observed attributes based on choice sets composed from consumer purchase observations.

Studies on how consumers behave (or appear to behave)

It is easy to imagine that a consumer's decision is heavily influenced by past experience either through habit formation or through variety seeking. Researchers have studied the dependency of past experience by using consumer panel data. Erdem (1996) analyzed data for four types of consumer goods (margarine, peanut butter, yogurt, and liquid detergent), he concluded that consumers are on average habit-persistent in all types asserted that ignoring this past-dependent

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[25] The retailer scanner dataset was not available from Nielsen while we run this study, but it became recently available this year. Extending this study with the data can be a nice future work.

behavior in choice models would bring about biases in model estimation. More recently, a study by Bronnenberg et al. (2010) matched observed purchase histories with the households' life histories such as state of birth, current state of residence, age at which they left their state of birth, and the number of years they have lived in current states. Then, they showed that consumers maintain the brand capital built up based on past experiences. Because of lacking number of observations per household, we could not consider this effect of past experience on lighting preferences. A study investigating this factor will be an interesting addition to our work once more data become available.

Hardie et al. (1993) looked at the past dependency issue from the perspective of prospect theory (reference dependency and loss aversion). By using panel data for refrigerated orange juice purchases, they showed that the model incorporating prospect theory had better fit and predictive capability than a classical MNL model. However, Hardie et al.'s study and other similar attempts to verify reference-dependent behaviors were later denounced by Bell and Lattin (2000) by pointing out that the measurement of loss aversion could be confounded with consumer heterogeneity in certain attributes.

Besides the issue of past dependency of preferences, studies also looked at the problem of consideration set (also known as choice set) formation (Roberts and Lattin, 1991; Siddarth et al., 1995; Chiang et al., 1998; Van Nierop et al., 2010). These studies point out the fact that consumers do not consider all the available alternatives for their final purchase decisions because of bounded rationality or other constraints. The subset of alternatives considered for the final decision is defined as a consideration set, which is normally not observed. For this reason, at the initial stage the consideration set issue has been studied through expensive and effort-taking surveys (e.g. Roberts and Lattin (1991)). Researchers have been looking for easier ways to handle this issue with panel data. Siddarth et al. (1995), for example, devised two methods (heuristic or Bayesian updating approach) to statistically estimate each household's unobserved choice sets (different across households), and extended them to allow dynamical updates of the sets over the observation period. They estimated probabilities that each product will belong to a household's choice set based on observed proportions of purchases of a certain alternative among total purchases of that product category during an initialization period (e.g. one year). By incorporating purchases during the following periods (after the initialization period), they could dynamically reconstitute choice sets for individual households. The limitation of this study is that it is only applicable to non-durable goods being frequently purchased.

Chiang et al. (1998) and Van Nierop et al. (2010) suggested models based on two-stage models separating a consideration stage and a choice stage. From the model, they estimate probabilities that each household can have any potential type of consideration sets. So instead of showing which specific consideration set is used by households, their models build upon probabilistic consideration sets. While the computational complexity of Chiang et al.'s method increases exponentially with total number of alternatives N (i.e. 2^N-1), that of Van Nierop et al.'s method increases linearly with N. These methods are still computationally challenging for cases like ours with a large number of alternatives while having relatively few observations per household. We instead adopt a simpler way of constructing consideration sets which is to combine alternatives that have been purchased within certain temporal and spatial boundaries. While this method requires a set of assumptions which can only be partially justified, it allows us to implement and interpret the model more easily. More details will be provided in the following method section.

5.3. Methods and data

Model formulation

We use the partial data that we selected for general service light bulb purchases from the original Nielsen data as explained in Chapter 4. We adopt a similar choice modeling method to the one used in the analysis in Chapter 3. As specified in that chapter, we model choices by a random utility model. The utility U_{ij} that consumer *i* draws from product alternative *j* is modeled as:

$$U_{ij} = V_{ij} + \epsilon_{ij} = \sum_{k=1}^{K} \left(\beta_k \cdot x_{ijk}\right) + \epsilon_{ij}, \tag{5.1}$$

where β_k is the preference coefficient for attribute k, x_{ijk} is the k-th attribute of alternative *j* subject *i*'s choice task, K is the number of observed attributes of alternatives, and ϵ_{ij} is the random error term, taken as an i.i.d. standard Gumbel distribution (Train, 2003). Multicollinearty can be a concern with the market data, but we observe that all variance inflation factors (VIF) of all three explanatory variables—price, watt, and type—are smaller than five. (O'brien, 2007)

Considering the large data size and time taken for model estimation, we use a multinomial logit model instead of a mixed logit (i.e. random coefficient) model. As in Chapter 3, we test the influence of both alternative-specific and customer-specific attributes on purchases of general service light bulbs. We control for customer-specific attributes provided by Nielsen: household income, type of residence, education, and marital status. In addition, we test the effects of other exogenous factors that may have affected sales purchases: the effect of retail channel types, the effect of a key retailer, and time effects. The time effects need to be considered because important events like the enactment of the EISA in 2007 which is unobserved in the data could have affected purchase behaviors. Also we consider the effect of CFL promotion by Wal-Mart. In 2007, Wal-Mart ran an ambitious nationwide campaign of selling 100 million compact fluorescent light bulbs (Barbaro, 2007; Wal-Mart, 2007). Wal-Mart announced the goal at the end of November 2006 (Wal-Mart, 2006) and achieved the goal by the end of September 2007. Wal-Mart installed special in-store displays, increased shelf space for CFLs, released educational materials, and also launched store-branded CFLs at lower prices than other brand products.

It should be noted that the rated-lifetime information of a product was not available in our dataset, and is confounded with the type variable, as CFLs and incandescent bulbs have very distinct ranges of product life. The type of light bulb may also be correlated with the color temperature as CFLs have generally a wider range of colors than incandescent ones. We recognize these confounding factors when interpreting the coefficients. Brightness is also unobserved in the original data, which is correlated with wattage levels. To accommodate this issue, an interaction term between type and wattage is included in the model estimation. This can be justified by an observation shown in Figure 5.1 that the two different lighting technologies show very different ranges of luminous efficacy (lumen output per watt).

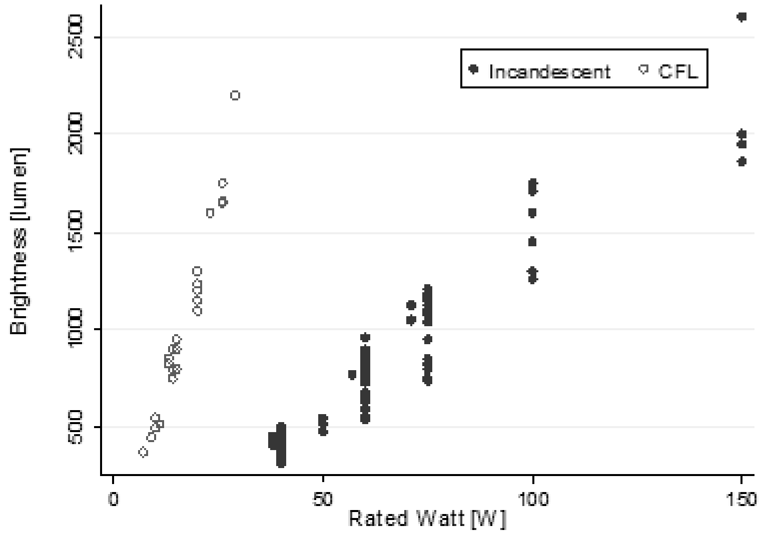

Figure 5.1 Relationship between rated wattage and brightness (in lumen) of all general service light bulbs observed in Nielsen data.[26] Each dot is for a light bulb product observed in the data.

Brand is separately coded as dummy variables for three major manufacturers: General Electric, Sylvania, and Philips. There are many other brands which are either store-specific or with small market share. They are treated together as a reference case for brand comparison. For the model with additional variables, effects of retailer types, income level, residence type, and education level are tested.

Modeling issues associated with an unobserved choice set

An important issue occurring from using sales data is that researchers do not have information on alternatives that were also available but not selected by consumers. Ideally, we would like to

[26] For about 5% of the light bulb items observed in the panel data, we could acquire technical details including lumen, life, socket type, etc. through scraping product data from online stores. Figure 5.1 is the relationship between watt and lumen attributes for those 5% of bulbs. The relationship appears linear, which can be estimated as:

$$Lumen = -186 + 167 \cdot d^{\mathrm{CFL}} + 16 \cdot watt + 46 \cdot d^{\mathrm{CFL}} \cdot watt,$$

where d^{CFL} is 1 for CFLs and 0 otherwise.

know the exact set of products that the consumer considered when making her final decisions. This set of alternatives is called a “consideration set” or a “choice set” in consumer choice literature (Roberts and Lattin, 1991). Attribute values of alternatives in the choice set are required for the estimation of a choice model. Since these are not available for our analysis, various assumptions need to be adopted to construct an assumed choice sets.

One source of information that we can use to estimate the consideration set is the information on purchases from other consumers, made in the same or nearby stores, and around the same time. We construct a choice set through this method by combining UPC observations from the available data. This requires the modeler to pursue decisions regarding the scope of UPCs to include in a consideration set. For example, the choice could include all purchased UPC observations ranging from across all retail chains or only from each individual chain where the observation is purchased. It could include all UPCs sold in each month or in a longer period of time, such as an entire year. In addition, the geographical scope could range from a choice set at the level of the entire nation or within each region (east, west, south, or central). States belonging to each region are shown in Figure 4.2. In a nutshell, the choice set will require considerations in terms of the time span, geographical region, and store type. The process of how we estimate the choice set is explained in the next section.

Choice set selection

When considering whether products from one or many store chains should be included in the choice set, the implicit issue that arises is whether we can assume that a consumer considers what to buy first and then decide where to visit to find the item, in which case the consumer’s consideration set is wider and not limited to a specific retailer store. For this purpose, we observe percentages of total expenditure spent on light bulbs at each shopping trip. If consumers normally choose from items displayed in a store where they visit to purchase some other products, we assume the relative percentage of spending on light bulbs when compared to all purchases is low.

The average of the percentage of total expenditure spent on light bulbs is 14%, and the median is 6%. The 75% percentile is 15%, which means that for 75% of all shopping trips involving light bulb purchases, money spent on light bulbs takes less than 1/7 of the total. The distribution of these percentage values is shown in Figure 5.2 for the shopping trips where consumers purchased light bulbs. This observation, though incomplete, can support that consumers consider which bulb product to choose after, not before, they arrive at a store. Based on this finding, we choose to construct the base case choice sets for each retailer chain.

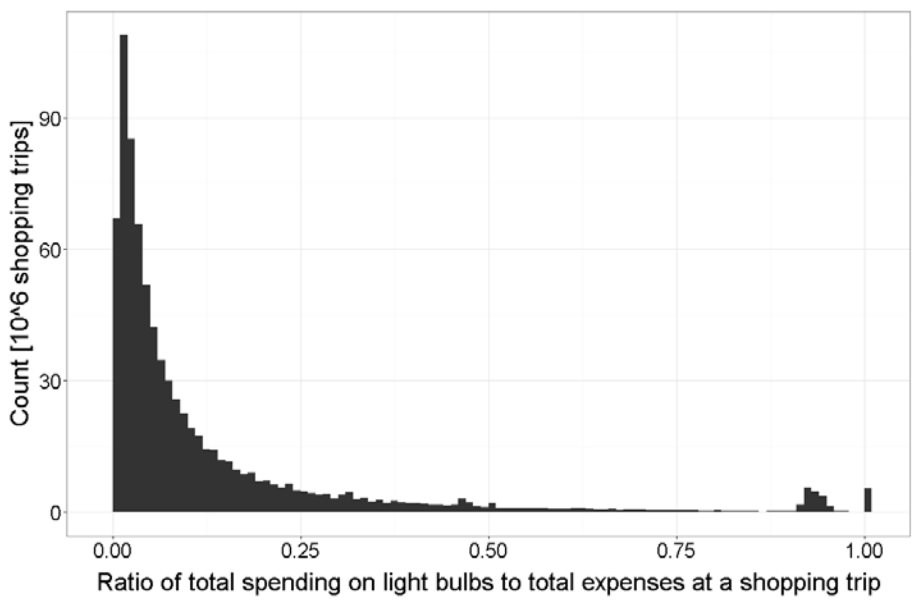

Figure 5.2 Distribution of percentage of total expenses spent on light bulbs at each shopping trip. This plot is only for the shopping trips involving light bulb purchases. The mean is at 0.14, and the median is 0.06. We can also observe at the right end that there are a small number of shopping trips mainly intended for light bulb purchases.

The items available in a store vary over time (from year to year, or from month to month, for example). One could then assume that the choice set should be constituted from all items sold in a month, or all items sold in a year. We decide to use a monthly choice set for the main model partly because we assume store items vary at least seasonally and also because the finding from Figure 5.2 suggests that people may not be able to consider items that were available months ago for a current purchase choice. However, it can be problematic as the monthly choice sets may include very few purchases, especially when the purchases are from small retailers, and therefore leading to a very small consideration set. When any monthly choice sets end up with only one UPC observation, we extend the consideration set for that retailer to include UPCs purchased during the whole year.

Another issue is whether stores of an identical retailer chain maintain similar set of items across the country, or whether products will vary by region. In order to account for this issue, we use a regional choice set, considering that products may vary by region at stores of a national chain.

Finally, in several instances, the same UPCs purchased within a given boundary may have a different price in different stores or as a result of a deal. Because it is not realistic for consumers and does exacerbate the IIA issue to have two identical products with two different price levels available in the same store at the time of their choices, we need to pick one among repetitive UPCs appearing in a choice set. We test two approaches to tackle this issue: 1) using the most common price level observed in the data for that UPC, or 2) use a random price selection based on equal probabilities assigned to each observed sale. The second method still gives a higher probability to a more common price level because the level appears more frequently in a choice set. There is no clear way to justify one way or the other. We decide to use the random method as a base case and observe how using the other affects the result. Table 5.1 summarizes the discussion in this section about the selection process of the choice set.

Table 5.1 Summary of choice set selection process

Issue	Dimension	Option	Choice	Justification
Which boundary to use to construct choice sets	Geographical boundary	State-/county-level	x	State- or county-level considerations cannot be considered because sample weights in the data can only be used to represent population at the regional or national level. Then we assume stores of an identical retailer chain can maintain different set of items across regions.
		Regional	o	
		National	x	
	Time span	Month	o	We assume items in stores can vary monthly or seasonally. Shoppers may not be able to consider items that were available months ago for a current purchase choice.
		Year	x	
	Store chains	All chains	x	We observe the average percentage of shopping expenses spent on light bulbs is low. We assume that this means consumers choose from items displayed in a store where they visit to purchase other products.
		Individual chain	o	
How to select a price level for identical UPCs in a given choice set		Most common price	x	One is not necessarily more justifiable than the other. We pick the random method as a base case which is simpler to implement and faster to run and test how using the other affects the result.
		Random pick	o	

Comparing stated and revealed preferences

In Chapter 3, we conducted a choice-based conjoint experiment for incandescent and compact fluorescent bulb choices to quantify the influence of factors that drive consumer choices based on the stated preference. We showed that providing operating cost information at the time of choice reduces consumers' implicit discount rate significantly, which will increase the adoption of energy efficient products.

Here, we compare the previous findings from the conjoint experiment with those from the consumer panel data in this chapter. (Hereafter, the former will be referred to as the stated preference (SP) model, and the latter as the revealed preference (RP) model.) We mainly compare willingness-to-pay (WTP) for light bulb attributes (watt and type) and implicit discount rates (IDR) consumers adopt for their purchases.

For the ease of interpretation of derived WTPs, we estimate multinomial logit (MNL) models from both SP and RP data with only main effects of the available bulb characteristics and a brightness term constructed from wattage and type variables.[27] Because the types of collected data are different between the two datasets, we cannot fully compare models based on the identical specification used in the SP model. The RP model for WTP estimation is:

$$U_{ij} = \beta_1 x_{ij}^{\mathrm{PRICE}} + \beta_2 x_{ij}^{\mathrm{WATT}} + \beta_3 x_{ij}^{\mathrm{TYPE}} + \beta_4 \hat{x}_{ij}^{\mathrm{BRIGHT}} + \beta_5 x_{ij}^{\mathrm{PKGSIZE}} + \epsilon_{ij}. \qquad (5.2)$$

To compare the estimates of implicit discount rates (IDR), we use a similar nonlinear model specification suggested in Chapter 3, which is:

$$U_{ij} = \beta_1 \left(\frac{\beta_2 (1+\beta_2)^{x_{ij}^{\mathrm{LIFE}}}}{(1+\beta_2)^{x_{ij}^{\mathrm{LIFE}}} - 1} x_{ij}^{\mathrm{PRICE}} + x_{ij}^{\mathrm{OPCOST}} \right) + \beta_3 x_{ij}^{\mathrm{TYPE}} + \beta_4 x_j^{\mathrm{PKGSIZE}} + \epsilon_{ij}, \qquad (5.3)$$

where the term within parentheses means equivalent annual cost, and β_2 directly represents the average discount rate which consumers implicitly adopt for their comparisons. Since life is not observed, we need to assume additionally that all CFLs constantly have 8000 hours of life (about 7 years assuming 3 hours of use/day) and incandescent lamps have 1000 hours of life (about 1 year). We also assume 10¢/kWh for average residential electricity price for the period between 2004 and 2009 to estimate annual operating cost of each bulb.

[27] Brightness $\hat{x}_{ij}^{\mathrm{BRIGHT}}$ is estimated through the equation in Footnote 26.

Since quite a few model specifications are used throughout this chapter to observe different aspects of the lighting preferences, Table 5.2 summarizes the model types we estimate. The numbers in the table refer to the indices of corresponding tables showing the model results. Each column represents different choice set types we test, and each row is for a type of model specification. The first column is for the widest choice set, and the last column is for the narrowest.

Table 5.2 Model types presented in this analysis. The numbers in the table refer to numbering of the tables with results that are included in this chapter.

			Choice Set Type			
		(Retailer)	all	individual	individual	individual
		(Time)	year	year	month	month
	Model Type	(Price)	most common	most common	most common	random
A:	Bulb attributes only w/o brand[a]					Table 5.8
B:	(A)+year+region+brand +demographic+retailer +channel type					Table 5.3[d]
B':	(Same as above)[b]		Table 5.4	Table 5.4	Table 5.4	Table 5.4
E:	Nonlinear (bulb attributes only)[c]					Table **5.7**

[a] The main purpose of this model is to estimate willingness to pay.
[b] To compare different choice sets, the four models in this row are estimated for East region only.
[c] The main purpose of this model is to estimate implicit discount rates.
[d] This is the main model our analysis focuses on.

5.4. Results and analysis

Understanding consumer choices for lighting technologies

Based on the narrow choice set, we estimate a multinomial logit model testing effects of attributes that potentially affect preferences for lamp technology type. Based on the observations from Chapter 4, our main model controls for time and regional effect, retailer types, effect of promotion by a key retailer (i.e. Wal-Mart), and other available demographic information. As we explained in Section 4.3, we could identify which retailer ID (provided by Nielsen) represents Wal-Mart by matching manufacturer codes included in UPC with a database of an international standards organization, GS1. In the main model, a dummy variable indicating CFLs sold in Wal-Mart is included and interacted with year dummies. The motivation behind this is that if interests in CFLs generally increased in 2007, it would not influence choices of CFLs specifically from Wal-Mart.

The main model in Table 5.3 shows that CFL type is preferred in the base case when all other attributes are kept constant. This can be partly because the type variable in the data is confounded with unobserved life and color attributes. Also, even though the coefficient for CFL type is positive, CFLs are not always preferred mainly because of higher price.

Wattage attribute is observed with a negative coefficient suggesting that consumers prefer lower energy consumption, while the interaction term between wattage and type showing the effect of brightness is not statistically significant. The SP model in Chapter 3 showed that there is a statistically significant quadratic relationship between brightness and consumer utility, which suggests that the fact that the linear interaction term is not significant does not necessarily mean consumers do not consider brightness for their choices. The size of the interaction term (0.00135) is a lot larger than the coefficient for wattage attribute (-0.000647), which suggests that consumers may prefer higher wattage for CFLs and lower wattage for incandescent bulbs. This is understandable considering that lower luminous efficacy of incandescent bulbs means that more power (i.e. higher energy bill) produces a little more light providing a net negative utility. On the other hand, for CFL, more power produces a lot more light bringing a net positive utility. CFLs from major manufacturers are preferred to those from other smaller manufacturers.

We observed in Chapter 4 that CFL sales have peaked in 2007. The main model shows that overall preference for CFLs over incandescent type gradually increased from 2005, peaked in 2007, and significantly dropped in 2008 and 2009. Preference toward CFLs from Wal-Mart increased very steeply in 2006 and 2007 and appears to stay near the peak level for the next two years. This suggests that the promotion of efficient bulbs by Wal-Mart in 2007 may be significantly related to the spike in CFL adoption in 2007 in addition to an increase in general awareness of CFLs and also that the effect is sustained even after the promotion ends. Several issues may be playing a role in decreasing CFL sales observed: since CFLs last longer, fewer purchases are needed over time to maintain the same lighting service. Or CFLs may already have filled a large part of the sockets that consumers intended to use CFLs in. Also, the EISA 2007 or other events around 2007 raised interests in CFLs, but over time consumers may have lost the interest in CFLs and looked for inefficient bulbs again.

The main model in Table 5.3 shows that among the six major channel types, as we could expect from the sales trend by channel types in Figure 4.8, CFL type is preferred in hardware stores and warehouse clubs significantly more than in discount stores. In dollar stores, drug stores, and groceries, incandescent types are preferred.

Among demographic variables, households whose heads have bachelor's degree prefer CFL type more than those who have not. Also, when compared with the lowest income households (<$20k/year), those with higher income (<$100k/year) prefer CFLs. But households with even higher income (>$100k/year) are not significantly different from the lowest income group. We observe that lower preference for CFLs is also related with a larger household size and whether they live in single-family houses. A potential explanation for this can be that households requiring more light bulbs prefer incandescent bulbs because of lower initial costs while not taking into account future operating cost savings.

Table 5.3 Main model including all relevant variables. The narrow choice set is assumed.

	β	*σ*
type=CFL	0.415	(0.0739)***
price_paid_per_bulb	-0.284	(0.00473)***
watt_nielsen	-0.000647	(0.000147)***
(type=CFL)*watt_nielsen	0.00135	(0.00113)
size1_amount	0.0140	(0.00143)***
base brand: Other		
GE	-0.273	(0.0106)***
GE_cfl	0.399	(0.0205)***
Philips	-0.525	(0.0203)***
Phil_cfl	0.322	(0.0428)***
Sylvania	-0.431	(0.0182)***
Syl_cfl	0.266	(0.0273)***
base year: 2004		
type=CFL & panel_year=2005	0.222	(0.0444)***
type=CFL & panel_year=2006	0.298	(0.0445)***
type=CFL & panel_year=2007	0.419	(0.0382)***
type=CFL & panel_year=2008	0.276	(0.0399)***
type=CFL & panel_year=2009	0.0953	(0.0416)**
WalMart_CFL	-0.706	(0.0854)***
WalMart_CFL & panel_year=2005	-0.235	(0.0974)**
WalMart_CFL & panel_year=2006	0.150	(0.0921)
WalMart_CFL & panel_year=2007	0.420	(0.0845)***
WalMart_CFL & panel_year=2008	0.366	(0.0865)***
WalMart_CFL & panel_year=2009	0.361	(0.0910)***
household_size*type=CFL	-0.123	(0.00693)***
base channel: Discount Store		
(major_channels=Dollar Store)*type=CFL	-0.452	(0.0514)***
(major_channels=Drug Store)*type=CFL	-0.222	(0.0492)***
(major_channels=Grocery)*type=CFL	-0.189	(0.0381)***
(major_channels=Hardware/Home Improvement)*type=CFL	0.333	(0.0379)***
(major_channels=Warehouse Club)*type=CFL	0.599	(0.0531)***
base marital status: Married		
(marital_status=Widowed)*type=CFL	0.0824	(0.0310)***
(marital_status=Divorced)*type=CFL	-0.0395	(0.0246)
(marital_status=Single)*type=CFL	-0.0405	(0.0257)
(region=Central)*type=CFL	0.0101	(0.0257)
(region=South)*type=CFL	-0.00294	(0.0249)
(region=West)*type=CFL	-0.0528	(0.0308)*
base type of residence: Mobile		
(type_of_residence=Multi-family)*type=CFL	-0.0801	(0.0452)*
(type_of_residence=Single-family)*type=CFL	-0.0958	(0.0370)***
(type_of_residence=Two-family)*type=CFL	-0.0534	(0.0571)
(bachelor=1)*type=CFL	0.0974	(0.0186)***
base income bracket: <$20k		
($20k<household_income<=$40k)*type=CFL	0.121	(0.0288)***
($40k<household_income<=$60k)*type=CFL	0.160	(0.0307)***
($60k<household_income<=$100k)*type=CFL	0.146	(0.0317)***
($100k<household_income<=$200k)*type=CFL	0.0299	(0.0366)
(household_income >$200k)*type=CFL	-0.131	(0.0942)
Observations	7,130,802	
Log-Likelihood	-1.810e+09	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Effect of selecting different choice sets

According to the discussion in the previous section, there can be many potential combinations of choice sets. So assuming a different choice set for model estimation can affect the model results. To see how the differences in choice sets affect model outcomes, we compare outputs from the same model specification as in Table 5.3 while adopting different choice sets. To make the comparison more compact and tractable, we focus only on *East* region data. We compare four types of choice sets starting from a model with the widest possible choice set and testing two more models by changing one dimension of the choice set at a time in a cumulative way. The choice set used for the first model (Model RP1) is all UPC observations from the entire year, across all retailer chains in East region, and the UPC redundancy is avoided through the most common price method. This is the largest choice set we test. Then, the second choice set used in Model RP2 is based on UPC observations within each month, while the other dimensions remain the same (across all retailer chains in East region, and the most common price method). The third choice set (Model RP3) has only the UPCs purchased from each retailer chain, in East region, and in a given month. A UPC with the most common price is selected. The last choice set in Model RP4 is for each retailer chain, in East region, and in a given month, while adopting the random price selection to avoid the UPC redundancy. These choice set types are summarized at the top of Table 5.4.

As we move from Model RP1 to Model RP4, the biggest difference between adjacent models occur between Model RP2 and Model RP3, where choice sets are composed at the individual retailer chain level. The sizes of the largest choice set for Model RP1 to Model RP4 are 826, 340, 51, and 51 respectively. (Model RP3 and Model RP4 have choice sets of identical sizes. The only difference between them is in price selection method.)

Model RP3 and Model RP4, based on choice sets for individual retailer chains, have fewer coefficients that are statistically significant because of the smaller number of observations in narrow choice sets. For example, effects of Wal-Mart or certain retail channel types are not significant any more. Also, we observe that signs of coefficients flip for some brand dummies and package size attribute in Model RP3 and Model RP4 while they do not for other variables. This is possible because, for example, a lot larger choice set in the first two models contains more large packages (e.g. 12-pack), which are not preferred to smaller packages by consumers even with lower price per bulb. These observations suggest that the change made between Model RP2 and Model RP3—whether to combine UPCs across all retailers or from individual ones—has a significant effect on model outcomes. Among the two price selection methods explained earlier, we do not see a significant difference between the results from the two methods according to Model RP3 and Model RP4.

Table 5.4 Basic models based on four different choice sets for East region. Each column is estimated with different levels of choice sets based on the same data. Types of each choice set are given on the top of the table. Regional effects are not available for this because this result is only for East region.

		Model RP1		Model RP2		Model RP3		Model RP4	
Choice set type	(Retailer)	all		all		individual		individual	
	(Time)	year		month		month		month	
	(Price)	most common		most common		most common		random	
		β	σ	β	σ	β	σ	β	σ
type=CFL		0.909	(0.157)***	0.809	(0.156)***	0.675	(0.165)***	0.741	(0.166)***
price_paid_per_bulb		-0.294	(0.00765)***	-0.139	(0.00728)***	-0.108	(0.00804)***	-0.144	(0.00848)***
watt_nielsen		-0.00340	(0.000287)***	-0.00287	(0.000307)***	-0.00214	(0.000342)***	-0.00208	(0.000343)***
(type=CFL)*watt_nielsen		-0.00613	(0.00218)***	0.00131	(0.00219)	-0.000511	(0.00233)	0.00101	(0.00234)
size1_amount		-0.0733	(0.00250)***	-0.0356	(0.00286)***	0.00662	(0.00308)**	0.00131	(0.00331)
GE		1.163	(0.0184)***	0.830	(0.0183)***	0.00957	(0.0212)	0.0171	(0.0213)
GE_cfl		-0.404	(0.0336)***	-0.464	(0.0335)***	0.111	(0.0411)***	0.141	(0.0413)***
Philips		0.447	(0.0337)***	0.0566	(0.0335)*	-0.299	(0.0420)***	-0.296	(0.0420)***
Phil_cfl		-0.153	(0.0751)**	-0.102	(0.0751)	0.101	(0.0832)	0.121	(0.0830)
Sylvania		0.865	(0.0226)***	0.576	(0.0224)***	0.151	(0.0303)***	0.157	(0.0303)***
Syl_cfl		-0.411	(0.0432)***	-0.450	(0.0429)***	0.00838	(0.0526)	0.0339	(0.0526)
type=CFL & panel_year=2005		0.258	(0.0779)***	0.112	(0.0777)	0.202	(0.0869)**	0.183	(0.0873)**
type=CFL & panel_year=2006		0.401	(0.0809)***	0.259	(0.0810)***	0.305	(0.0886)***	0.275	(0.0891)***
type=CFL & panel_year=2007		0.804	(0.0682)***	0.536	(0.0682)***	0.337	(0.0752)***	0.317	(0.0756)***
type=CFL & panel_year=2008		0.923	(0.0696)***	0.674	(0.0695)***	0.331	(0.0768)***	0.310	(0.0772)***
type=CFL & panel_year=2009		0.498	(0.0710)***	0.420	(0.0710)***	0.160	(0.0796)**	0.128	(0.0799)
WalMart_CFL		-0.629	(0.171)***	-0.632	(0.170)***	-0.337	(0.173)*	-0.318	(0.174)*
WalMart_CFL & panel_year=2005		0.223	(0.200)	0.231	(0.200)	-0.185	(0.205)	-0.194	(0.205)
WalMart_CFL & panel_year=2006		0.496	(0.193)**	0.495	(0.193)**	-0.248	(0.198)	-0.271	(0.198)
WalMart_CFL & panel_year=2007		0.619	(0.172)***	0.617	(0.172)***	-0.0511	(0.176)	-0.0845	(0.176)
WalMart_CFL & panel_year=2008		0.348	(0.177)**	0.353	(0.177)**	-0.164	(0.180)	-0.192	(0.181)
WalMart_CFL & panel_year=2009		0.691	(0.184)***	0.688	(0.184)***	0.149	(0.187)	0.131	(0.188)
household_size*type=CFL		-0.131	(0.0149)***	-0.131	(0.0149)***	-0.138	(0.0158)***	-0.137	(0.0158)***
(major_channels=Dollar Store)*type=CFL		-1.430	(0.110)***	-1.439	(0.109)***	-0.0921	(0.119)	-0.0965	(0.119)
(major_channels=Drug Store)*type=CFL		-0.852	(0.0862)***	-0.861	(0.0860)***	-0.285	(0.0924)***	-0.288	(0.0930)***
(major_channels=Grocery)*type=CFL		-0.991	(0.0706)***	-0.997	(0.0704)***	0.0602	(0.0775)	0.0486	(0.0779)
(major_channels=Hardware/Home Improvement)*type=CFL		0.715	(0.0731)***	0.704	(0.0729)***	0.298	(0.0789)***	0.316	(0.0793)***
(major_channels=Warehouse Club)*type=CFL		1.765	(0.0957)***	1.771	(0.0961)***	0.285	(0.110)***	0.238	(0.111)**
(marital_status=Widowed)*type=CFL		0.0309	(0.0620)	0.0314	(0.0621)	0.0467	(0.0669)	0.0463	(0.0671)
(marital_status=Divorced)*type=CFL		-0.138	(0.0515)***	-0.139	(0.0515)***	-0.158	(0.0550)***	-0.157	(0.0551)***
(marital_status=Single)*type=CFL		-0.298	(0.0494)***	-0.298	(0.0495)***	-0.293	(0.0531)***	-0.293	(0.0532)***

(region=Central)*type=CFL								
(region=South)*type=CFL								
(region=West)*type=CFL								
(type_of_residence=multi-family)*type=CFL	-0.417	(0.110)***	-0.409	(0.109)***	-0.363	(0.115)***	-0.360	(0.115)***
(type_of_residence=single-family)*type=CFL	-0.457	(0.103)***	-0.451	(0.102)***	-0.443	(0.108)***	-0.445	(0.108)***
(type_of_residence=two-family)*type=CFL	-0.370	(0.115)***	-0.359	(0.114)***	-0.370	(0.121)***	-0.374	(0.121)***
(bachelor=1)*type=CFL	0.177	(0.0375)***	0.178	(0.0375)***	0.154	(0.0400)***	0.155	(0.0401)***
($20k <household_income ≤$40k)*type=CFL	0.0108	(0.0597)	0.0111	(0.0596)	-0.0306	(0.0630)	-0.0334	(0.0632)
($40k <household_income ≤$60k)*type=CFL	0.117	(0.0565)**	0.113	(0.0565)**	0.0583	(0.0599)	0.0564	(0.0601)
($60k <household_income ≤$100k)*type=CFL	0.0215	(0.0522)	0.0234	(0.0522)	0.00196	(0.0551)	0.00126	(0.0553)
($100k <household_income ≤$200k)*type=CFL	-0.1000	(0.0736)	-0.106	(0.0735)	-0.120	(0.0783)	-0.126	(0.0785)
(household_income >$200k)*type=CFL	-0.410	(0.129)***	-0.419	(0.129)***	-0.413	(0.145)***	-0.416	(0.144)***
Observations	36,865,077		14,102,540		829,919		829,919	
Log-Likelihood	-8.450e+08		-7.260e+08		-3.270e+08		-3.270e+08	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

How can we compare two choice models based on revealed and stated preference data?

Willingness to pay

We estimate WTPs from SP and RP data using MNL models (Table 5.8 and Table 5.9 in the appendix) including only the main effects of light bulb attributes to derive population average WTPs. To control for the effect of unobserved brightness information in the RP model, we include brightness values estimated from the relationship shown in Figure 5.1 and Footnote 26 instead of the interaction term between type and wattage which was originally used for the main model in Table 5.3. This is because having the estimated brightness term enables easier interpretation of the result. The result is summarized in Table 5.5.

Table 5.5 Comparison of willingness-to-pay for changes in two main attributes: type and watt when all other attributes are held constant. RP and SP represent revealed and stated preference data. We should note that because of confounding between observed and unobserved attributes, the WTP-RP value for type is likely to represent combined WTPs for type and all correlated changes (e.g. life or color).

		WTP - RP		WTP - SP	
Attribute	Δ(attribute)	Mean	95% CI	Mean	95% CI
Type	CFL over incandescent	$1.84	(1.68, 2.00)	$2.37	(1.57, 3.18)
Watt	10W increase	-$0.06	(-0.08, -0.03)	-$0.37	(-0.51, -0.24)
Brightness	100 lumen increase	$0.02	(0.00, 0.033)	$0.16	(0.10, 0.23)
Life	1000 hour	N/A[a]		$0.50	(0.38, 0.62)
Color	CCT=3700K or 5000K (base=2700K)	N/A[a]		Not significant	

[a] Life and color data were not available in the RP data set, and these attributes may be confounded with type, watt, or brightness.

We should note that because of the unavailability of life and color attributes in the panel data, the WTPs for type change in SP and RP case are not directly comparable. The RP model suggests that consumers are willing to pay $1.84 more for a change from an incandescent bulb to a CFL, holding watt and brightness constant. However, there may be other attributes, such as life and color, that are correlated with type but for which we lack data. Thus the WTP for type in the RP data captures the effect of type plus these potentially correlated attributes. A separate WTP for type only cannot be derived from the panel data. The WTP for CFL type in the SP model was \$2.37. In this case, because all other attributes observed by the respondent are known and controlled for, the value represents WTP for type alone, holding all other attributes in the experiment constant (including watt, brightness, life, and color). The fact that the WTPs for CFL type is positive does not mean consumers always choose CFLs over incandescent ones because these WTP estimates assume all other attributes are constant. In real choices, the price difference between a CFL and an incandescent lamp can easily be larger than the WTP for CFL type. For wattage variable, a WTP for 10W increase is -\$0.06 for the RP model, while the corresponding WTP for a 10W increase for the SP model was observed at -\$0.37. These negative WTP values mean that consumers prefer lower wattage when all other attributes are equal.

From the findings above, it appears that the stated preference (SP) model yields consistently larger WTPs (in absolute magnitude) than the revealed preference (RP) model does. A potential reason is that the price coefficient in the SP model is underestimated because the compensation given at the end of the experiment depended on a choice made in an unknown choice task during the choice experiment, which might well induce participants to behave less sensitively to price variable in order to receive more expensive item as the compensation.

Implicit discount rate

To reduce the computational burden, we focus on a representative state within each region for implicit discount rate (IDR) comparison. To justify this approach, we test a model (Table 5.10 in the appendix) without weighting factors using the same model specification of the model in Table 5.3. Even though the weighting factors in Nielsen data cannot be used to represent state-level population, we see that the model *without* weighting factors yields close results with the model estimated *with* weighting factors. Based on this observation, we present state-level model outputs, while not worrying about representativeness.

From Central, West, and South region, we pick Ohio, California, and Texas because these states have the largest number of observations in the panel data. For East region, we choose Pennsylvania partly because it has the second largest number of observations and also because our SP model is also based on the experiment performed in Pittsburgh, Pennsylvania. The result is summarized in Table 5.6. We see that the ranges of discount rate values from the two different dataset are comparable, suggesting the results are robust. Detailed model results used for IDR estimation is given in Table 5.7. The IDR values for stated preference data shown in the last two columns are directly from Table 3.4.

Table 5.6 Comparison of estimates of implicit discount rates based on revealed and stated preference data

	Revealed Preference				Stated Preference	
	Pennsylvania	California	Texas	Ohio	Operating cost shown	Operating cost not shown
Implicit discount rate	260% (0.3%)	330% (0.1%)	230% (0.5%)	290% (0.9%)	100% (22%)	560% (70%)

Standard errors in parentheses

Table 5.7 Models for implicit discount rate (IDR) estimation. Each column is for a representative state from each region.

	East - Pennsylvania		West - California		South - Texas		Central - Ohio	
	β	σ	β	σ	β	σ	β	σ
Equivalent annual cost	-0.042	(0.00019)***	-0.043	(0.0017)***	-0.12	(0.00028)***	-0.085	(0.00021)***
Implicit discount rate	2.58	(0.0028) ***	3.32	(0.0011)***	2.26	(0.0054)***	2.85	(0.0089)***
type=CFL	-0.092	(0.0013) ***	0.17	(0.0016)***	-0.29	(0.00069)***	-0.15	(0.00042)***
Package size	0.013	(0.0011) ***	-7.0e-5	(0.0027)	-0.025	(0.000034)***	0.0063	(0.000020)***
Brightness ($\times 10^3$ lumen)	0.016	(0.0020) ***	0.025	(0.0019) ***	0.60	(0.00092) ***	0.46	(0.0021) ***
Purchase observations	15,417		21,100		33,235		21,439	
Log-Likelihood	-37,828		-50,749		-103,905		-60,487	

Standard errors in parentheses

All IDR estimates here are higher than 200%, suggesting that, during the observation period, the barriers to energy efficient lighting were considerably high. Among the four states, Texas exhibits the smallest IDR of 230%, while California has the largest of 330%. According to the panel data, California has the highest CFL adoption rate among the four states, which is about 40% of all bulb purchases between 2004 and 2009, while Ohio has the lowest rate of 25%. Thus, we observe that the differences in the adoption rates are not directly explained by the IDR estimates, which is possible when the bulb choices are determined more by other factors such as type preferences or price sensitivity than by expected savings.

All the IDR values sit between 100% and 560%, the two point estimates from the SP model shown in the last two columns of Table 5.6. One of the reasons for this finding can be that some light bulb packages were still providing annual operation cost information voluntarily between 2004 and 2009. This was likely to have influence on bringing the IDRs between the level where 100% packages were assumed to have such information and the level where the cost information is not present at all. Moreover, subjects in the SP experiment could be less sensitive to monetary values such as future savings because of the hypothetical setup, and there are missing attributes that may be confounded with the attributes used to measure IDR.

5.5. Conclusion and policy implications

We analyzed consumer preferences for light bulbs based on revealed preference data. We found that consumers prefer lower price in general, but preference for wattage depends on bulb types (CFL or incandescent). At an identical price level, consumers prefer CFLs to incandescent bulbs, but the large price difference keep CFLs from being purchased. We also observed that the peak in CFL adoption in 2007 was significantly related to the increase of CFL sales by Wal-Mart, which in turn could potentially be linked to its nationwide promotion campaign for CFL the same year. From the findings, we can argue that the well-directed efforts through major retailers might have a significant effect on higher adoption of energy efficient lighting.

Although the estimates of willingness-to-pay for changes in type and wattage are not directly comparable due to the unobserved attributes in the panel data, we observed that the signs matched. The willingness-to-pay values for CFL type over incandescent one and for lower energy consumption were found to be positive when other attributes are held constant, which is consistent with the finding from the conjoint experiment.

The implicit discount rates estimated in four representative states were in a range from two to four hundred percent similar to the values from the conjoint experiment. The large size of discount rates indicates that barriers to energy efficient lighting carry on during the period we observed.

Appendix

This appendix presents three tables estimated to support the discussion in the result section. Table 5.8 and Table 5.9 are basic models involving only main effects of light bulb attributes based on RP and SP data respectively, which were used to estimate willingness-to-pay for those attributes. Table 5.10 is used to justify that the model results estimated with and without weighting factors, especially for the main effects of bulb-specific attributes, are within a similar range. The purpose is to ensure the range of our discount rate estimates will be robust because the model for estimating implicit discount rates is at the state level which cannot be represented with the weighting factors provided in the panel data.

Table 5.8 Basic RP model with only the main effects of bulb-specific attributes. Willingness-to-pay estimated from this model can be interpreted in a more straightforward way.

	β	σ
Type	0.575	(0.0270)***
price_paid_per_bulb	-0.312	(0.00483)***
watt_nielsen	-0.00177	(0.000428)***
brightness (x10^3 lumens)	0.0572	(0.0234)**
size1_amount	-0.00137	(0.00144)
Observations	7,130,802	
Log-Likelihood	-1.820e+09	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.9 Basic SP model with only the main effects of bulb-specific attributes.

	β	σ
Type	0.345	(0.0489)***
price_paid_per_bulb	-0.146	(0.0141)***
watt_nielsen	-0.00539	(0.000846)***
brightness (x10^3 lumens)	0.233	(0.0424)***
life (x10^3 hours)	0.0729	(0.00534)***
CCT=3700K	-0.0771	(0.0564)
CCT=5000K	0.0621	(0.0550)
Observations	6,552	
Log-Likelihood	-2187.9	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.10 Model without using weighting factors provided by Nielsen. This is the same model specification used in our main model given in Table 5.3. The results of the main model is copied in the second column for ease of comparison. The coefficients and significance of the two models are close to each other.

	Unweighted		Weighted – our main model	
	β	σ	β	σ
type=CFL	0.533	(0.0476)***	0.415	(0.0739)***
price_paid_per_bulb	-0.261	(0.00253)***	-0.284	(0.00473)***
watt_nielsen	-0.000963	(0.000101)***	-0.000647	(0.000147)***
(type=CFL)*watt_nielsen	0.00248	(0.000680)***	0.00135	(0.00113)
size1_amount	0.0169	(0.00112)***	0.0140	(0.00143)***
base brand: Other				
GE	-0.199	(0.00660)***	-0.273	(0.0106)***
GE_cfl	0.341	(0.0128)***	0.399	(0.0205)***
Philips	-0.417	(0.0136)***	-0.525	(0.0203)***
Phil_cfl	0.183	(0.0263)***	0.322	(0.0428)***
Sylvania	-0.365	(0.0123)***	-0.431	(0.0182)***
Syl_cfl	0.160	(0.0170)***	0.266	(0.0273)***
base year: 2004				
type=CFL & panel_year=2005	0.181	(0.0288)***	0.222	(0.0444)***
type=CFL & panel_year=2006	0.271	(0.0277)***	0.298	(0.0445)***
type=CFL & panel_year=2007	0.446	(0.0249)***	0.419	(0.0382)***
type=CFL & panel_year=2008	0.294	(0.0258)***	0.276	(0.0399)***
type=CFL & panel_year=2009	0.00631	(0.0266)	0.0953	(0.0416)**
WalMart_CFL	-0.895	(0.0582)***	-0.706	(0.0854)***
WalMart_CFL & panel_year=2005	-0.0284	(0.0674)	-0.235	(0.0974)**
WalMart_CFL & panel_year=2006	0.415	(0.0617)***	0.150	(0.0921)
WalMart_CFL & panel_year=2007	0.569	(0.0582)***	0.420	(0.0845)***
WalMart_CFL & panel_year=2008	0.473	(0.0590)***	0.366	(0.0865)***
WalMart_CFL & panel_year=2009	0.479	(0.0614)***	0.361	(0.0910)***
household_size*type=CFL	-0.111	(0.00439)***	-0.123	(0.00693)***
base channel: Discount Store				
(major_channels=Dollar Store)*type=CFL	-0.444	(0.0319)***	-0.452	(0.0514)***
(major_channels=Drug Store)*type=CFL	-0.249	(0.0293)***	-0.222	(0.0492)***
(major_channels=Grocery)*type=CFL	-0.225	(0.0226)***	-0.189	(0.0381)***
(major_channels=Hardware/Home Improvement)*type=CFL	0.290	(0.0225)***	0.333	(0.0379)***
(major_channels=Warehouse Club)*type=CFL	0.636	(0.0319)***	0.599	(0.0531)***
base marital status: Married				
(marital_status=Widowed)*type=CFL	0.0305	(0.0202)	0.0824	(0.0310)***
(marital_status=Divorced)*type=CFL	-0.0468	(0.0160)***	-0.0395	(0.0246)
(marital_status=Single)*type=CFL	-0.0335	(0.0169)**	-0.0405	(0.0257)

(region=Central)*type=CFL	-0.0299	(0.0162)*	0.0101	(0.0257)
(region=South)*type=CFL	-0.0386	(0.0156)**	-0.00294	(0.0249)
(region=West)*type=CFL	-0.106	(0.0186)***	-0.0528	(0.0308)*
base type of residence: Mobile				
(type_of_residence=multi-family)*type=CFL	-0.144	(0.0289)***	-0.0801	(0.0452)*
(type_of_residence=single-family)*type=CFL	-0.142	(0.0237)***	-0.0958	(0.0370)***
(type_of_residence=two-family)*type=CFL	-0.138	(0.0361)***	-0.0534	(0.0571)
(bachelor=1)*type=CFL	0.0631	(0.0108)***	0.0974	(0.0186)***
base income bracket: <$20k				
($20k <household_income ≤$40k)*type=CFL	0.0864	(0.0194)***	0.121	(0.0288)***
($40k <household_income ≤$60k)*type=CFL	0.0662	(0.0202)***	0.160	(0.0307)***
($60k <household_income ≤$100k)*type=CFL	0.0496	(0.0208)**	0.146	(0.0317)***
($100k <household_income ≤$200k)*type=CFL	-0.0371	(0.0243)	0.0299	(0.0366)
(household_income >$200k)*type=CFL	-0.237	(0.0562)***	-0.131	(0.0942)
Observations	7,130,802		7,130,802	
Log-Likelihood	-817,485		-1.810e+09	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Policy implications, conclusions and future work

In this thesis, two major issues related to energy efficient lighting were closely investigated. First, the system-wide effects of lighting retrofits were analyzed at each building level incorporating interactions between energy consumption from different end-uses. Second, consumer preferences for lighting technologies were observed and analyzed based on two types of data: experimental data designed to observe the effect of additionally given cost information; and consumer panel data containing household purchase records over a 6-year period.

System-wide effects

The heat replacement effect of switching to more efficient lighting system for single-family detached houses across the U.S. was investigated on three aspects: net primary energy consumption, CO_2e emissions, and savings in energy bills. This work contributes to the literature by providing the first regional analysis of this effect for the U.S. residential sector based on realistic lighting consumption data. The findings suggest that as the U.S. electricity grid becomes less carbon intensive, this effect associated with changes in heating and cooling demands may become more prominent and worthy of consideration. When considering expected *total savings* in energy or carbon emission, the heat replacement effect of the moderate lighting efficiency interventions we assumed in the analysis was not negligible depending on climate or regional fuel mix for electricity generation. However, the moderate interventions resulted in a small *overall* effect in magnitude. The heat replacement effect corresponded at most to around 1 percent of either *total* emissions or of energy consumption by a house. This study confirms that this effect exists and can be larger in some regions but is not a major reason not to adopt efficient bulbs.

A potential future work is to examine this effect at a wider scale. The current work was limited to a building level, and a study covering the entire building stock with more realistic scenarios and proper handling of uncertainties will provide more important implications for policy makers.

Consumer preferences and choices

First, using a choice-based conjoint experiment, the effect of product and consumer attributes on consumer choice for light bulbs were examined. Two conditions were considered where annual operating cost estimates are either disclosed or withheld. Providing operating cost information induces stronger preferences for bulbs with longer lifetime and lower energy consumption. Showing operating cost information also decreased implicit discount rates (IDRs) from over 560% to around 100%. These two findings suggest that the new FTC labeling rule, mandating provision of annual operating cost, is a helpful measure fostering more adoption of efficient lighting technologies. Very large IDRs among low-income consumers were observed implying that lower income consumers present a particularly large barrier to adoption.

Second, using consumer panel data, we observed that light bulb sales are decreasing almost monotonically over the period between 2004 and 2009, while CFL sales gradually increased until 2007 and then decreased in following years. Corresponding to these observations, we showed from the choice model estimated from the panel data that the nationwide promotion of CFLs by Wal-Mart in 2007 is potentially related to the CFL adoption peak in 2007 in addition to the effects of the EISA or other factors/programs around the year. Implicit discount rates estimated from the stated and revealed preference data (i.e. experimental and market data) were observed in a similar high range suggesting that consumers value up-front purchase cost savings much higher than future energy cost savings – so high that it is inconsistent with how they treat future savings in other contexts.

These works are unique in that no choice models or discount rates have been estimated for the lighting sector, and that the method we adopted to estimate the IDRs has not been tried in other existing choice models. Comparing the findings using both the SP and RP data is a challenging task and has not been attempted for lighting products before. Our contribution also includes the visual presentation and interpretation of the lighting product consumption trends and patterns directly retrieved from the consumer panel data over a six-year period. An interesting extension of this work will be investigating the effect of past experiences on lighting choices once more observation points per household over a longer period of time become available.

Combining our findings from this thesis, we argue that the new energy efficiency labeling on light bulb packages needs to be continued. Also, while the labeling can help facilitate adoption of efficient light bulbs, we see other types of barriers persist, which is reflected in the high implicit discount rates observed even with the information given on the label. The EISA of 2007 is expected to be helpful in reducing those barriers by removing alternatives from the choice set but is also seen as an overreach by many consumers.

Moreover, knowing that light bulb sales are from a few large retailers and that their promotion activities are likely to facilitate higher adoption of efficient bulbs, governments can consider incentives directed to retailers such as linking sales (or sales ratio) of energy efficient bulbs (or other products) with business tax benefits.

Extending the lessons learned from the HRE study, we also suggest that when certain energy efficiency measures are designed or assessed, potential interactions among the proposed measure and other components in the system should be identified and taken into account. While the average effect of the interaction on the final outcome can be small, certain conditions that can lead to large deviation from the average should at least be considered.

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