Uncertainty in Lightbulb Failing: A Study on the Energy Paradox within the U.S. Residential Lighting Market

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Abstract

"The energy paradox", which describes the rather slow adoption of energy-efficient products despite their savings potential, has been observed in the U.S. residential lighting market for LED products. With LED sales fall short of traditional incandescent bulbs, this paper looks at how uncertainty, specifically regarding lightbulb's probability of failing, could explain the paradox. We deploy a discrete choice model to replicate consumer's decision making, and then use Monte Carlo simulation to find income level of the consumer who is indifferent between buying incandescent and LED. With the presence of lightbulb failing uncertainty, we found that consumers who discount future by a little (with discount factor around 0.9) already prefer incandescent over LED for majority of times, resulting in the paradox. Predictions are made for average U.S. consumer's purchasing behavior, and future studies are suggested to validify our theoretical framework.

I. Introduction

When selecting an investment to purchase among several near-perfect substitutes, our rational minds argue that finding the product with the lowest present discounted price is all we need. As simple as it sounds, this is not the whole story. Although newer products come with better technologies and higher efficiencies that save money in the long run, their more expensive price tags often distort consumer preferences. Specifically, products that promise future savings but come with high investment costs struggle to be adopted by end users, at least while the purchasing price remains high. This phenomenon is especially pronounced in the energy market, to the point that a special term, "the energy paradox", has been named for it (Jaffe and Stavins 1994). Specifically, "the energy paradox" describes the gradual adoption of energy-efficient products, which may have high investment costs but come with low future recurring charges, usually in the form of electricity bills.

To examine the cause behind "the energy paradox", this paper considers how uncertainty in energy-efficient product's performance affect consumer decision making. We focus on two main players within the U.S. residential lighting market: incandescent and light-emitting diode (LED) lightbulbs. A typical incandescent lightbulb consumes 60 watts of electricity per hour, whereas the LED equivalence (that is, the LED lightbulb that generates the same amount of light) usually consumes only 10 watts of electricity per hour. While LED being more energy-efficient and having significantly longer lifespan compared with incandescent, it has yet to be widely adopted among residential consumers. This paper intends to study how uncertainty in lightbulb performance, specifically on the lightbulb failing probability, affects consumer purchasing decision, which may serve as an explanation to "the energy paradox".

To evaluate the uncertainty factor, this paper proposes a discrete choice model to examine "the energy paradox" theoretically. We introduce a finite-period expected utility function to measure consumer's payoff from buying incandescent and LED lightbulbs. Uncertainty in lightbulb failing is modelled as a probability figure, which affects the expected utility level. Then, discrete choices are made by comparing the expected payoff for buying either type of lightbulb, and choosing the one with the higher value. To solve this model by finding the income of the indifferent customer (that is, the customer who derives the same amount of utility from buying incandescent and LED lightbulbs), we use the Monte Carlo method.

Simulation run by Monte Carlo suggests that even if consumers discount future payoffs slightly (having discount factor of about 0.9), the indifferent customer's income already reaches the upper bound. This means that the existence of failing probability indeed affects how consumer perceives which lighting product is more preferable. Based on our model, we also make predictions on what pricing scheme will make an average U.S. consumer more likely to purchase LED product. Among three pricing scenarios that we tested, pricing LED at the same level as incandescent seems to work the best.

Before discussing more on our methodology and results, it is important to recognize the prevalence of "the energy paradox" phenomenon and four common theories and hypotheses proposed by other literatures in attempt to investigate its cause. Most cases that fit in "the energy paradox" follow the same pattern as the one described by Jaffe and Stavins (1994): the adoption rates for more energy-efficient products fall well below economists' predictions, despite the ample availability of these products on the market. For instance, Hausman (1979) studies the 1975 and 1976 survey data for air conditioner purchases, during which years consumers are more concerned with energy costs due to the 1973 oil crisis. He estimates that when faced with delayed energy savings, an average consumer undervalues the future savings at a rate of about 25 percent, predicting slow adoption for energy-efficient air conditioners.

Gately (1980) follows up on Hausman's study with the refrigerator market. He compares three brands of refrigerators, each with a cheaper-to-invest low-efficiency model and a more-expensive-to-invest high-efficiency one. The result shows that the implicit discount rate for high-efficiency refrigerators are about one-half of the low-efficiency: ranging from 45 to 130 percent for refrigerators operating at 3.8 cents per kilowatt-hour (kwh), and from 120 to 300 percent for the ones operating at 10 cents per kwh. The low discount rate for energy-efficient refrigerators again indicates that consumers weight more on present over future.

In more recent literature, Klemick et al. (2015) conduct interviews on managers of 43 heavy-duty trucking firms to investigate reasons behind the slow adoption of more fuel-efficient heavy-duty trucks. Although most firms choose to purchase new tractors and are able to afford the more fuel-efficient models, they are still reluctant to select the energy-efficient options on the market.

For this paper, "the energy paradox" in the lightbulb market has been observed since its introduction by Jaffe and Stavins (1994), regardless of some structural changes within the market itself. For instance, different from the late twentieth century, the most energy-efficient player in the lightbulb market has shifted from CFLs to light-emitting diode (LED). While the price of CFLs has been decreasing throughout the past decade, in the year of 2015, the U.S. Department of Energy finds the percentage of household owning CFLs lamps still fall short compared with incandescent: 33.2% for CFLs and 34.6% for incandescent (Buccitelli, et al. 2015). "The energy paradox" trend also starts to exhibit on LED bulbs. LED has been adopted for residential lighting use since 2011 in the U.S. (LED Market Intelligence Report 2015). Despite having even longer lifespan and lower energy consumption compared with CFLs, in the year of 2015, LED bulbs sold only accounts for 6.7% of the total sale of lighting related products (Buccitelli, et al. 2015). Though information on LED savings are readily available in the form of Energy Star label, significant market acquisition for LED has not been observed until production costs begin to decrease (LED Market Intelligence Report 2015).

While the existence of "the energy paradox" is well established, its cause behind remains unclear. Four most common theories and hypotheses are 1) externalities resulted market failures, 2) imperfect information on energy savings, 3) underweighting the energy consumption factor, and 4) uncertainty about technology performance. Jaffe, Newell and Stavins (2005) made the case for externalities. Multiple forms of market failure are discussed as mechanisms behind "the energy paradox", including limitation on how much upfront investment can be made, high "learn-by-using" transaction costs for adopting new technologies, and network externalities where adoption becomes more valuable only when others also start using it. They argue that with the presence of these externalities, consumers see the externalities as costs bundled with energy-efficient products, thus are driven towards older and less energy-efficient options. While their speculation is justified on a theoretical basis, Jaffe, Newell and Stavins did not provide any quantitative result to support their hypothesis; as unobservable as the nature of externalities, evaluating these externalities' contribution to "the energy paradox" remains a challenge.

With market failures being hard to quantify, Allcott and Taubinsky (2015) turns to behavioral approach in attempts to measure the effect of imperfect information. In their paper, Allcott and Taubinsky set consumer's willingness to pay (WTP) level as their target, and then look at how WTP has changed when presented with energy savings information for buying CFLs by designing two experiments: one computer based, the other in store. In the online experiment, consumers are asked to choose between purchasing CFL and incandescent bulbs, and then some treatment groups receive supplementary energy-saving information before repeating the decision-making sequence. For the in-store experiment, consumers are approached to fill out a lighting-related survey which records their knowledge on CFLs' saving potential. In exchange, consumers receive coupons on buying lightbulbs, and the coupon value and coupon usage depicts changes in their WTP. While the two experiments' samples are not necessarily from the same population, they both show that information supplementation does not seem to affect customer's WTP at a statistically significant level; price instead plays the driving force in decision making. But considering the methodology deployed by Allcott and Taubinsky, we cannot completely rule out information as a potential candidate. For instance, participants in the online experiment are self-enrolled, and the in-store experiments are only conducted in three major U.S. cities on the east coast (Boston, New York, and Washington, D.C.). This indicates that the sample selected could potentially be biased. And in Dharshing and Hille's (2017) study on how information affects Switzerland household's decision for investing in energy-efficient home renovation products, they find that information plays an important role for people who are less impulsive to make a purchase, and for people who are more risk averse. Hence, information's effect on decision making may not be for the general public, but instead for a subset of individuals.

With the role of information being unclear, some begin to speculate the role of energy saving itself as a significant decision-making factor. Turrentine and Kurani (2007) interviewed 57 Californian households in hope of assessing fuel economy's contribution to the decision-making process of vehicle purchases. They find that energy efficiency as a factor is undervalued among many households: in fact, about one-fourth of the interviewed households do not track their monthly or annual fuel spending at all. Some believe that the high price of fuel-efficient vehicles is a conspiracy, and some places high value on owning certain types of non-fuel-efficient vehicle. Although an argument can be made that the 57 Californian household sample may suffer from severe selection bias, this paper illustrates that energy savings might not be a major element for consideration in consumer's decision making; they weight more on other factors of an energy-consuming product, which helps explain "the energy paradox" phenomenon.

At last, the fourth major theory considers high uncertainty in energy-efficient product's performance as a factor to explain "the energy paradox." Concepts such as risk aversion and loss aversion are built in as part of consumer's utility function, and are used to explain consumer choices. For example, Greene (2011) factors in a loss-averse framework developed by Tversky and Kahneman (1992) when modeling consumer present value function for vehicle purchase, where the potential losses come from performance uncertainty towards fuel-efficient vehicles. By running Monte Carlo simulation, Greene finds that a typical, loss-averse consumer would have a negative expected present value when choosing vehicles with high fuel economy, suggesting that consumers are less likely to purchase fuel-efficient cars given their uncertainty towards fuel-efficient car's performance.

Among the four theories behind "the energy paradox", performance uncertainty seems to have more validity given its focus on the energy-efficient product itself, which falls in line with consumer's undervaluation of energy consumption. For this reason, we focus on the uncertainty factor when examining the low adoption of LED lightbulbs in the U.S. residential lightbulb market.

The rest of the paper is laid out as the following. Section II explains the discrete choice model we construct, and how Monte Carlo simulations are deployed. Section III describes the parameters used in the Monte Carlo simulation: how data is gathered to model parameter distributions, and how estimations are conducted. Section IV presents all results we find from running Monte Carlo simulations. Section V offers prediction on an average U.S. consumer's purchasing decision, and then discusses the robustness of our findings. Section VI concludes the paper, restates the results, and suggests topics for future research.

II. Methodology

a. Discrete Choice Model

To reproduce consumer's decision making on lightbulb purchase, we construct the following model. The agents in our model are U.S. consumers who are interested in buying one new lightbulb for residential use. We will consider multiple time periods, but our reference point is always the starting time when a lightbulb is purchased. Consumer will receive certain level of utility from purchasing incandescent lightbulbs, and from purchasing LED lightbulbs. In a discrete choice environment, consumer compares the utility for buying each type of lightbulb, and then chooses the one that offers a higher level of utility. Given the existence of lightbulb failing uncertainty, consumer's utility is modeled as an expected value function. We first consider the baseline two-period case:

$$E[U_k] = u(Y - C_k - \mathcal{E}_k) + \delta \cdot [p_k \cdot u(Y - C_k - \mathcal{E}_k) + (1 - p_k) \cdot u(Y - \mathcal{E}_k)] \qquad (1)$$

In equation (1), $E[U_k]$ stands for the expected utility from buying lightbulb k, where k is either incandescent lightbulbs (INC) or LED lightbulbs (LED); u is a concave utility function; Y denotes consumer's income; δ is the discount factor, which is drawn from $(0, 1]$ (the closer δ is to 1, the more patient consumer is towards future savings; δ is limited to not be 0, otherwise it would make our study trivial by eliminating all future periods); p_k is the failing probability for lightbulb k; C_k is the cost of purchasing lightbulb k; $\mathcal{E}_k$ is the electricity cost of using lightbulb k, which is calculated by

$$\mathcal{E}_k = P_{elec} \cdot h \cdot W_k \tag{2}$$

In equation (2), P_{elec} represents the per unit electricity cost (unit: dollars per kilowatts); h denotes the number of hours a household keeps their lightbulb on; W_k is the level of energy consumed per hour by using lightbulb k (unit: kilowatts per hour). Notice that W_k can also be interpreted as the level of brightness generated by using specific lightbulb k, since the more energy a lightbulb consumes, the brighter it becomes.

Our expected utility function describes the following scenario. In the first period, consumer will purchase lightbulb k, and then immediately install the lightbulb in their household. Hence, consumer has to pay for both the lightbulb cost C_k and its electricity cost $\mathcal{E}_k$. In the second period, consumer will first discount charges incurred in this future time by a factor of δ, then consumer is faced with two scenarios. With probability p_k, lightbulb k they purchased in period one will burn out; consumer has to go out and buy the exact same lightbulb again, then still immediately install the lightbulb bought for illumination. With probability $(1 - p_k)$, the lightbulb bought in period one will keep functioning, so consumer only needs to pay for the electricity cost $\mathcal{E}_k$. After writing the second period's costs in the expected form, consumer's two-period expected utility function becomes equation (1).

With the help from equation (1), consumer begins making choices. Consumer first calculate the expected payoff for buying incandescent and LED lightbulbs, which are $E[U_{INC}]$ and $E[U_{LED}]$, respectively. Then, consumer compares these two expected payoffs. If $E[U_{INC}] > E[U_{LED}]$, consumer will purchase an incandescent lightbulb; if $E[U_{INC}] < E[U_{LED}]$, consumer will purchase a LED lightbulb; if $E[U_{INC}] = E[U_{LED}]$, consumer is indifferent between buying either type of lightbulb, so consumer may make a decision based on a coin flip.

All variables in equation (1) and (2) are exogenous, given that none is determined by our utility function. Among these variables, δ, h, and W_k can be changed based on consumer preferences: consumer can make a conscious choice on how much to discount charges incurred in the future, how long to keep a lightbulb on in their household, and what level of brightness they desire from the lightbulb. We also assume perfect information in our model, so that consumers can fully perceive each lightbulb's parameters when making decisions.

The purpose of this paper is to study how the existence of lightbulb failing probability p_k affects consumer's decision making. In our two-period baseline model, p_k does not change over time, since it is only included in the second period. In a more realistic environment, we would consider that p_k increases as time increases. As time approaches lightbulb k's theoretical lifespan, p_k will gradually reaches 1. For simplicity, we assume that lightbulb will certainly burn out at its theoretical lifespan, so p_k at its last time period will equal to 1. To account for such assumptions, we extend the two-period model to a finite horizon of two years:

$$E[U_k] = u(Y - C_k - \mathcal{E}_k) + \sum_{t=2}^{2\times 365} \delta^{t-1} \cdot \begin{bmatrix} p_k \cdot \left(1 + \dfrac{m_k(t - aT_k)}{T_k}\right) \cdot u(Y - C_k - \mathcal{E}_k) + \\ \left(1 - p_k \cdot \left(1 + \dfrac{m_k(t - aT_k)}{T_k}\right)\right) \cdot u(Y - \mathcal{E}_k) \end{bmatrix} \tag{3}$$

Two things are different for this finite-period expected utility function. One, in order to correctly sum up the discounted utility up to two years, we introduce T_k and a to our model. T_k represents the number of days a lightbulb k can be used, and it is fairly simple to calculate: we use lightbulb k's theoretical lifespan (in hours) divided by number of operating hours h to obtain an estimated figure (unit: days). a denotes the number of times we run through T_k during the two-year span;

that is, whenever t modulo T_k yields 0 (as in t can be divided by T_k with no remainder), then in the next time period, the value of a increases by 1. Based on this definition, the a value at the end of the two-year span represents number of lightbulb k consumer has bought, and thus a is restricted in $[0, (2 \times 365)/T_k]$, where it can only take integer values.

The other difference in this finite-period model is the inclusion of m_k, a constant to adjust for changes in lightbulb failing probability. We suppose that lightbulb k will certainly burn out at the end of its theoretical lifespan T_k. Hence, whenever the current running time of the lightbulb bought has reached T_k, we would like to adjust the lightbulb failing probability to be equal to 1. For this reason, m_k is calculated so that $(1 + m_k) \cdot p_k = 1$. It is worth emphasizing that the assumption on lightbulb k failing absolutely at time T_k and increasing at a liner rate are both made for simplicity. In reality, factors such the daily operating time of the lightbulb, the environment the lightbulb is operating under, and the lamp lightbulb is installed on will all affect lightbulb's actual lifespan, and it would also not be surprising if lightbulb's failing probability grows exponentially towards it theoretical lifespan instead of linearly, but we will ignore these scenarios in our theoretical framework.

What remains now is to specify the form of utility function u. We suppose that consumers will experience diminishing return on utility, and hence choose a simple square root function to capture this quality. On top of everything, given the magnitude of Y compared with other costs figures, we suspect the expected utility for each type of lightbulb may vary only on the decimal scale, making the comparison between $E[U_{INC}]$ and $E[U_{LED}]$ a bit tricky. To address this issue, we perform a monotonic transformation by multiplying both expected payoffs by 1,000. This would keep the ranking between two utilities, while making it easier to compare since the differences between two expected utilities have been magnified. Thus, the final form of the expected utility function we will use in our discrete choice analysis is

$$E[U_k] = \left(\sqrt{Y - C_k - \mathcal{E}_k} + \sum_{t=2}^{2\times 365} \delta^{t-1} \cdot \left[\begin{array}{l} p_k \cdot \left(1 + \frac{m_k(t - aT_k)}{T_k}\right) \cdot \sqrt{Y - C_k - \mathcal{E}_k} + \\ \left(1 - p_k \cdot \left(1 + \frac{m_k(t - aT_k)}{T_k}\right)\right) \cdot \sqrt{Y - \mathcal{E}_k} \end{array} \right] \right) \times 1000 \quad (4)$$

in which $k \in \{INC, LED\}$.

Based on equation (4), we suppose that consumer calculates both $E[U_{INC}]$ and $E[U_{LED}]$, then do the same comparison as we mentioned in the two-period case to determine which lightbulb to purchase. This completes our discrete choice model.

With this discrete choice framework, we are hoping to locate the consumer who is indifferent between buying incandescent and LED products. That is, we want to find the Y value of the consumer who has $E[U_{INC}] = E[U_{LED}]$. We henceforth denote the Y solution to $E[U_{INC}] = E[U_{LED}]$ as the "Y cutoff," and this Y indeed serves as the cutoff point: given that our expected utility function is monotonically increasing, for any consumer with $Y > Y$ cutoff, they are better off buying LED products; and for anyone with $Y < Y$ cutoff, they are better off with incandescent products. Hence, if we can track how this Y cutoff changes when changing other parameters in the expected utility function, we can find how consumer preferences change based on the existence of lightbulb failing uncertainty.

Given the difficulty to directly solve for such Y cutoff by equating $E[U_{INC}]$ with $E[U_{LED}]$, and our uncertainty on the exact value of p_k for each lightbulb type k, we introduce Monte Carlo simulation in the following sections to help search for such Y cutoff. We will also input different C_k, W_k, h, and δ values to our expected utility function, which allows us to investigate how Y cutoff is affected by changes made in these exogenous variables.

b. Monte Carlo Simulation

Monte Carlo is a type of computational algorithm that produces numerical results through repeated random sampling. If the problem we are interested in is deterministic in essence, but accompanied by some level of randomness that can be modeled as a probability distribution, we can then use Monte Carlo method to run the problem for a large number of times. Eventually, by law of large numbers, the simulated result will converge to the deterministic core that we are looking for.

There are two main reasons behind why Monte Carlo method is chosen for our study. One, traditional algebraic method for solving the Y cutoff by equating $E[U_{INC}]$ with $E[U_{LED}]$ is too complicated for our form of expected payoff function. Since we are summing over a finite period of times, and each period has our variable of interest Y built in, the form of our expected utility function becomes complicated very quickly. Hence, it is infeasible to solve for Y cutoff using traditional mathematical approach. Two and more importantly, while we can estimate our failing probability p_k through some literature, we do not know the exact value of p_k. However, we can model p_k as some probability distribution, and then random sample a p_k value for each lightbulb k during simulation. We can repeat such random sampling for a large amount of time, making our Y cutoff converge to its supposedly true value by law of large number. This is exactly what Monte Carlo simulation is good at, so we end up taking this approach.

The deterministic value that we are looking for is the indifferent consumer's Y cutoff. This Y cutoff point should exist, since if we take income (Y) to be large enough (say, passing a certain point $\hat{Y}$), then for all $Y > \hat{Y}$, the absolute difference between the expected utility of buying incandescent and LED becomes the following:

$$|E[U_{INC}] - E[U_{LED}]|$$

$$= 1000\left|\sqrt{\hat{Y} - C_{INC} - \mathcal{E}_{INC}} + \sum_{t=2}^{2\times365} \delta^{t-1} \cdot \left[\begin{array}{l} p_{INC} \cdot \left(1 + \frac{m_{INC}(t - aT_{INC})}{T_{INC}}\right) \cdot \sqrt{\hat{Y} - C_{INC} - \mathcal{E}_{INC}} + \\ \left(1 - p_{INC} \cdot \left(1 + \frac{m_{INC}(t - aT_{INC})}{T_{INC}}\right)\right) \cdot \sqrt{\hat{Y} - \mathcal{E}_{INC}} \end{array}\right]\right.$$

$$\left. - \sqrt{\hat{Y} - C_{LED} - \mathcal{E}_{LED}} + \sum_{t=2}^{2\times365} \delta^{t-1} \cdot \left[\begin{array}{l} p_{LED} \cdot \left(1 + \frac{m_{LED}(t - aT_{LED})}{T_{LED}}\right) \cdot \sqrt{\hat{Y} - C_{LED} - \mathcal{E}_{LED}} + \\ \left(1 - p_{LED} \cdot \left(1 + \frac{m_{LED}(t - aT_{LED})}{T_{LED}}\right)\right) \cdot \sqrt{\hat{Y} - \mathcal{E}_{LED}} \end{array}\right]\right| < \epsilon \qquad (5)$$

Since equation (5) holds for all $\epsilon > 0$, we can take $\hat{Y}$ as the Y cutoff point, proving the existence of the Y cutoff that we are interested in.

The number of simulation we run for our study is 500. Ideally, we should run an even larger number of trials to guarantee convergence to true value, but 500 simulations are already considerably large, so our findings are not heavily biased. Before each round of simulation, we specify four main variables that we control for: cost of buying lightbulb k (C_k), discount factor (δ), daily lightbulb operating hours (h), and type of incandescent lightbulb needed (W_{INC}, or interpret as level of brightness needed from the lightbulb). The LED lightbulb that produces the same level of brightness, W_{LED}, can be found using a conversion function (the energy consumed by certain type of incandescent lightbulb can be translated for LED lightbulbs, so there is no need of specifying the equivalent type of LED as replacement for incandescent. We will explain more about this in the next section). These four variables make certain of all parameters customer face when choosing between lightbulbs, so the only source of uncertainty is the lightbulb failing probability p_k.

The process of finding the Y cutoff is the following. For simplification, we limit the search range of Y to be within 10 to 100,000 dollars per year. This is a reasonable assumption.

Consider that the U.S. real median individual income is \$31,099 in 2016 (U.S. Bureau of the Census 2017), \$100,000 is a high enough upper limit to include the entire middle-class population whose preferences on lightbulb matters for our study. We will also assume people with more than \$100,000 annual income to be indifferent between buying incandescent and LED, given the high level of disposable wealth they own. By this simplification, \$100,000 is going to be the highest cutoff point in all scenarios. In each trial of simulation, a random cost of buying an incandescent and LED bulb is generated. Then, the simulation will search income level ranging from \$10 to \$100,000, and record the point at which buying LED generates the same level of utility as buying incandescent.

To make our program run more efficiently, we make the income sequence gap between \$10 to \$100,000 to be \$100, so that we are instead recording the first income level that generates a higher or equivalent utility for buying LED than buying incandescent ($E[U_{LED}] \geq E[U_{INC}]$). Although this approach makes our finding less precise, it dramatically speeds up the simulation; and with the \$100 gap being relatively small comparing to the upper income bound \$100,000, we tolerate such imprecision for the benefit of running more rounds of simulations.

The result of Monte Carlo simulation is a vector containing 500 income cutoff point Y of each random p_k generated for lightbulb k. We take the average among these Y, and treat it as the Y cutoff under the parameters we control for.

III. Parameters for Monte Carlo Simulation

a. Lightbulb Failing Probability

The essential element of our study is the inclusion of lightbulb k's failing probability p_k. The failing mechanism behind incandescent and LED differs significantly. Incandescent lightbulbs generate lights based on the coil or filament of tungsten wire inside; and while it generates lights, it also emits a considerable amount of heat. Since coil and tungsten evaporate under high heat, incandescent bulbs stop working when evaporation is so severe that electric connection can no longer be maintained (Gluck and King 2008). In contrast to incandescent, LED emits very little to no heat at all, so its electric components inside usually will not fail because of excessive heat (LED Lighting n.d.). The light LED generates depends on individual red, green, and blue electronic lighting components, and due to the sophisticated technology deployed on each lighting component, LED will fail when any component stops functioning.

To find each lightbulb's failing probability for our analysis, we ideally would use consumer's perceived failure rates of incandescent and LED over a two-year span. However, such data is not easy to obtain. We choose to fall back on the second-best option, which is to use the observed or actual failure rates of incandescent and LED to approximate p_k.

Given that LED's failing mechanism depends on which component fails first, we could theoretically model each component's running time as an expoential random variable, and hence by exponential races, LED's running time parameter will be the sum of all its component's exponential parameter. But since it is hard to measure how long each component will continue functioning, we choose to instead use a more empirical estimating method. A study done by Casamayor, Su and Sarshar (2015) surveyed Belgium, Germany, Spain, and UK households on the actual LED lifespan experienced and found that around 31.71% of the sample encountered LED failure during the first year of use. Two main critics naturally arise from using this 31.7% data to approximate LED failing probability. One, the survey subjects are not U.S. households, who are the focus of our study. Two, the surveyed failure rate is different from the failing probability we are interested in, particularly because it is generalized for the entire first-year period, rather than points of time within a year. For problem one, due to the homogeneity of LED products worldwide, we assume that using non-U.S. data is acceptable. For problem two, we acknowledge the weakness of this data: if time increments are small, then the actual failing probability should be close to the failure rate during the small time period. However, with no better option available to us, we fall back to this data as the failing probability for LED, and round it up to 30% for simpler calculation.

In terms of incandescent bulbs, no similar experiment is found during our research period. However, incandescent lightbulbs have been commercialized since the late 19th century (Matulka and Wood 2013), so its production have been perfected for more than a hundred years. We take the long existence of incandescent lightbulbs into our consideration, and use equation (6) to estimate incandescent's failing probability as 15%:

$$p_{INC} = \frac{365 - \frac{INC\ theoretical\ lifespan}{median(h)}}{365} \tag{6}$$

In equation (6), $INC\ theoretical\ lifespan$ is about 1500 hours, which is the median of estimations provided by department of energy (How Energy-Efficient Light Bulbs Compare with Traditional Incandescents n.d.); $median(h)$ is the median amount of hours a household keeps a lightbulb on, which is about 5 hours according to Casamayor, Su and Sarshar (2015). The number calculated is 17.8%, and we round this up to 15% to adjust for consumer's familiarity with incandescent products. Notice that it has the same concern as our approximation for LED failing probability, mainly being that the probability is generalized to the entire first-year period. We again acknowledge such critics, and proceed with this 15% estimation since it is the best we can do during our research period.

To input these two figures into our Monte Carlo simulation, we choose to model both p_{LED} and p_{INC} as normally distributed, with $p_{LED} \sim \mathcal{N}(0.3, 0.1)$ and $p_{INC} \sim \mathcal{N}(0.15, 0.05)$. One assumption made in here is for the standard deviation of this two probability measures: we do not know the actual standard deviation of these two failing probabilities. While taken into account that consumers are more familiar with incandescent products, we choose incandescent's failing probability to have an arbitrarily smaller variation than LED's. When drawing p_k from these two distributions in each round of simulation, we also check that $p_{LED} \geq p_{INC}$ holds; if not, we will redraw the LED's failing probability until this condition is satisfied. This step is done so that consumers is more uncertain towards LED product's performance, which is in line with "the energy paradox" theory that we intend to test.

b. Lightbulb Costs

To acquire data on lightbulb costs, we decide to gather empirical data from two major U.S. merchandize stores, Target and Walmart, and then take the average as our lightbulb cost. All data are gathered on March 31, 2018, from search results on each retailer's website. We first exclude several outliers in our sample: some advanced, high-tech incandescent and LED bulbs have significantly higher costs than the rest observed. To prevent these outliers from distorting the mean, we limit most of incandescent samples to have per unit price below 6 dollars, and the LED samples to below 10 dollars.

The cost data we end up using is the per unit cost: if a lightbulb is sold in a package of two identical bulbs, we divide its listed price by two to obtain a single unit's cost. This is done because our study is interested in consumer buying one lightbulb for residential use. By dividing the number of units in one package to get the unit price, we are assuming that lightbulbs can always be purchased individually. This is, however, not a realistic assumption. Empirical data gathered from Target and Walmart shows that lightbulbs are usually sold in bundles, commonly in a package of two to four. Hence, consumers are not necessarily faced with the unit price of each lightbulb, but rather the bulk price of buying several at the same time. We choose to only consider unit prices for the purpose of this study, but readers should beware that the higher bulk purchasing price can certainly distort consumer preferences when selecting lightbulbs.

Parts of cleaned data and its descriptive statistics can be found in Table 1 and 2. The overall feature is that LED lightbulbs cost more: LED lightbulbs are, on average, about one to two dollars more expensive than incandescent. Prices of LED products also tend to have larger variation compared with incandescent's.

When running Monte Carlo simulation, we will take C_{INC} and C_{LED} based on the specified W_{INC} parameter. This is because lightbulb costs vary when it has different brightness level. We will also explore how different pricing scheme could affect consumer's Y cutoff when they are more uncertain about LED's performance. In our results section, we will take lightbulb costs as 1) market suggested price, 2) LED consistently being one dollar more expensive than incandescent, and 3) LED having the same price level as incandescent. This is done so that we can evaluate how prices affect consumer decision when they are more uncertain about LED lightbulb's performance: if we would like to facilitate the transition from incandescent to LED, price is the most effective tool suppliers and social planners can target.

c. Energy Costs

As shown in equation (2), the electricity cost on a lightbulb is determined by three factors: per unit electricity price (P_{elec}), number of daily operating hours for a lightbulb (h), and level of energy consumed per hour by using lightbulb k (W_k). For P_{elec}, we treat it as a fixed constant. This is not an over-simplification, given that the average electricity price across the U.S. has only increased from 9.83 cents per kwh in 2010 to 10.27 cents per kwh in 2016 (U.S. Energy Information Administration 2018). This is only a 4% increase over a more-than-five-year span, and the amount increased is low enough to be assumed as having no impact on a normal U.S. household.

In terms of h, since it is one of four variables that can be controlled, we can assign different values to h. In this paper, we set h to be at four different levels: 1 hour, 5 hours, 10 hours, and 15 hours. This means that consumers can keep their lightbulb on for a minimum of averaging 1 hour per day, up to averaging 15 hours per day. We will look at how different choice of h affects our Y cutoff result.

As mentioned before, we only need to specify W_{INC} when running the simulation, since W_{LED} will automatically be specified given our choice of W_{INC}. There are four common types of incandescent lightbulbs on the market: 40W, 60W, 75W, and 100W. We will set the type of incandescent lightbulb consumer is interested in before each round of simulation, and then use a conversion between W_{INC} and W_{LED} to find the equivalent type of LED consumer may consider buying. The conversion can be found in Table 3. Given that W_{INC} is also a controlled variable, we will evaluate how changes in W_{INC} affect our Y cutoff result.

IV. Results

a. Market Price Scenario

We first examine the case where both LED and incandescent's pricing scheme is taken from the Target and Walmart sample. Figure 1 depicts Y cutoff levels for buying either 40, 60, 75, or 100 Watts incandescent lightbulb or its equivalent LED product, controlled for consumers leaving their lightbulbs on for 1, 5, 10, and 15 hours per day, and having discount factor ranging from 0.80 to 1. The interpretation of each point on the graph is the following: at the same discount factor (δ), daily operating hours (h), and lightbulb brightness level (W_{INC}), individuals with income above the point will always prefer buying LED over buying incandescent, and individuals with income below the point will always prefer buying incandescent over LED.

While for all four W_{INC} specified, Y cutoff points converge to the income upper bound \$100,000 as discount factor decreases, the 40 and 75 Watts lightbulb products seem to converge more quickly than 60 and 100 Watts. This might be related to the data we gathered. From Table 1 and 2, we see that the differences of mean unit price between 40 Watts incandescent and LED equivalence, and between 75 Watts incandescent and LED equivalence, are more pronounced than for 60 and 100 Watts lightbulbs. Specifically, for 40 Watts product, incandescent is more than \$2 dollars cheaper than LED's; for 75 Watts product, the gap grows to about \$3. At the same time, both 60 and 100 Watts incandescent lightbulbs are only \$1 to \$1.5 dollars more expensive than LED counterparts. With the larger cost difference, only consumers with high income and are more patient towards future savings would consider LED as the preferable purchase. Notice that the price difference also gives weight to us evaluating C_k in different scenarios: as cost of buying lightbulb changes, consumers that are more uncertain towards LED products clearly respond differently to various cost level.

If we treat consumers to have lightbulb daily operating hours to be the average among the four levels we tested, the pointwise graph of Figure 1 transforms to Figure 2, which is a line graph. Figure 2 more clearly demonstrates an important finding: regardless of the desired level of brightness from buying a lightbulb, as long as consumers slightly discount the future (for discount factor around 0.925 to 0.95, or as in being 5% to 7.5% impatient towards future savings), then consumers with income at or below $100,000 will always find incandescent lightbulb more preferable than LED. Since most consumers are not this little impatient towards future benefits, only a small fraction of consumers with high-level income would purchase LED products over incandescent. This is in line with what we observe from "the energy paradox" in the lighting market.

b. LED Being One Dollar More Expensive Than Incandescent

Figure 3 and 4 describes the scenario where consumers are faced with $C_{LED} = C_{INC} + 1$ regardless of δ, h, and W_{INC}. Figure 3 with its pointwise graph depicts how the Y cutoff point converges at different h level. At all levels of W_{INC}, we observe that people leaving their lightbulb on for longer periods at a daily basis have lower Y cutoff points at the same δ and W_{INC} level. While this result is also present in the previous market price case, it is easier to observe in this "one dollar more" scenario.

This relationship between Y cutoff and h is expected: for consumers who keep the light on in their house for longer periods, charges on electricity are more pronounced. Given LED's significant energy savings, individuals with higher demand for lights will balance LED's higher failing uncertainty with its higher energy savings. Hence, as number of daily operating hour increases, the Y cutoff point in general decreases.

The relationship between W_{INC} and Y is, on the other hand, unexpected. We speculate that Y cutoff would decrease as W_{INC} increases, but Figure 3 does not support such claim. This might be that energy savings mostly come from daily operating hours h: while switching to LED saves more for consumers desire a higher level of brightness, only when the consumer leaves their lightbulb on will the savings be generated. Hence, while fixing h and δ, W_{INC} does not have a statistically significant impact on our Y cutoff.

Similar to what we have done for the market price case, by considering all consumers leaving their lights on at the average length, we average out all points in Figure 3 and arrive at Figure 4. In Figure 4, we again observe that Y cutoff converges to its upper bound when discount factor δ dips below 0.925 for all levels of W_{INC} we controlled for. What differs from Figure 2 is that, since now the difference between C_{LED} and C_{INC} is consistently held at 1, we no longer observe a rather abrupt convergence for the 40 and 75 Watts incandescent and their equivalent LED lightbulbs.

c. LED and Incandescent Having Same Price

Figure 5 and 6 describes the case where $C_{LED} = C_{INC}$. Just as the "one dollar more" scenario, we see that Y cutoff clearly decreases as h increases, holding δ and W_{INC} at fixed levels. What differs is the range of Y cutoff points we found, and how fast it converges. When consumer almost fully perceives future savings (that is, having discount factor δ close to 1), we see that apart from consumers with $h = 1$, almost everyone would view LED lightbulb as the better purchase between the two. Additionally, with prices between LED and incandescent being the same, more consumers are likely to purchase LED products. This is because from Figure 6 (consumers with average h value), the Y cutoff points do not converge until δ is lower than 0.85, and for δ within 0.85 to 1, the lowest Y cutoff we observe is much lower than the "one dollar more" case. Hence, as price of LED reaches incandescent's level, more people would find LED product more preferable.

V. Discussion

a. Prediction for Average U.S. Consumer

Using our theoretical model, we can technically predict when an average U.S. consumer would purchase LED lightbulb over incandescent. From Figure 2, 4, and 6, we already graphed the relationship between Y cutoff and δ at average h level, holding W_{INC} fixed. To make prediction, we would like to know the average income Y value within the United States.

To more precisely acquire such data, we turned to Current Population Survey (CPS). CPS is a monthly survey conducted on U.S. households regarding employment related measures. It is administrated by U.S. Census Bureau and the Bureau of Labor Statistics (Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset].). For our study, we used the March Annual Social and Economic Supplement data in 2017, and extracted variable "INCTOT" that records an individual's total pre-tax income from the previous year. In other words, we are acquiring U.S. individual's yearly pre-tax incomes of the year 2016.

After deleting missing data, our sample size becomes 144,462. The mean income level of this sample is $40,497.04. In Figure 2, 4, and 6, we have drawn a horizontal dashed red line to denote this income level.

On Figure 2, we observe that the average income level does not have any intersection with the Y cutoff line, which suggests that under the current market price level, an average U.S. consumer would not purchase LED product at any discounting factor. This prediction is consistent with "the energy paradox": when consumers are more uncertain towards LED products, only people earning high income would balance out the uncertainty with its potential benefits, and has LED products generate higher utility than incandescent. As a result, early adoption of LED is slow, which is what we have been observing.

Now we consider reducing LED's price to a lower level. Figure 4 is reducing LED's price so that it is one dollar more expensive than incandescent. While this price reduction may seem significant, our theoretical model suggests that an average U.S. consumer still would not purchase LED products, unless they can fully perceive future savings ($\delta = 1$); even with so, the average income line only intersects with the lower end of Y cutoff line's pointwise confidence interval. Hence, to have an average U.S. consumer more likely to purchase LED products, we need to further reduce its cost. Figure 6 illustrates the scenario where $C_{LED} = C_{INC}$. Under this case, an average U.S. consumer with discount factor higher or equal to 0.975 would prefer LED over incandescent. While this preference is still held by a fraction of average U.S. consumers, we already have significantly more consumers choosing LED products instead. For average U.S. consumers with discount factor lower than 0.975, if manufacturers or social planner would consider buying LED lightbulbs as an efficient outcome, then discriminatory pricing or subsidy programs can be deployed so that $C_{LED} < C_{INC}$ for these consumers. This would then push LED to be more widely adopted by U.S. residential consumers.

b. Robustness

Under our proposed discrete choice model, one major finding is the relationship between discount factor δ and Y cutoff. Although we expect impatient consumers to be more willing of buying incandescent over LED, we did not expect Y cutoffs to converge so quickly to our upper income limit – at discount rate around 0.9. However, we should acknowledge several limitations within our framework that could jeopardize the model's robustness.

One big assumption we had is the distribution of failing probability p_k. In order to run Monte Carlo simulation, we estimated means for p_{LED} and p_{INC}, then arbitrarily assigned different standard deviation values and chose p_k's distribution as normal. While the figures we estimate seem reasonable under the hypothesis that consumers are more uncertain towards LED product's performance, we do not know whether our p_{LED} and p_{INC}'s distribution is true. Hence, the numerical values of Y cutoff we estimated may be off from its true value, leaving our theoretical model only suitable for estimating direction of changes instead of precise level of changes.

Two, we mentioned that all consumers with income higher or equal to our upper bound \$100,000 are considered as indifferent between LED and incandescent purchases. Without the support from empirical data, this assumption is made quite arbitrary. If we increase this upper bound to \$150,000, the numerical results we obtained from Monte Carlo simulation might differ. Hence, the prediction we gave on section V (a) may not be accurate.

Three, a slight amount of time inconsistence exists within our theoretical framework. While the C_k data are taken in March 2018, many other parameters are taken from study conducted in between 2015 and 2016. Given lighting market's fast-changing pace, this time gap may cause bias in the numerical results produced.

Another concern regards our three costs scenarios. We see that reducing C_{LED} to be one dollar more expensive than C_{INC} seem to have limited impact on reducing Y cutoff point. In reality, consumer may become more and more risk-neutral or even risk-seeking in response to smaller and smaller C_{LED} and C_{IND} gaps, meaning that when LED products are only a bit more expensive than incandescent, consumer would begin to prefer LED even with its higher failing probability. Our theoretical model, unfortunately, does not capture this possibility, which again would affect the robustness of our prediction in section V (a).

Additionally, our methodology is stripped-down generalization from real world problems. As mentioned in the section I, Turrentine and Kurani's (2007) Californian household survey suggests that energy consumption might not be an important factor for consumers to consider. Consumers can attach certain feelings toward incandescent or LED products: maybe some prefer the color of lights generated by incandescent bulbs, so failing uncertainty is not a deterministic factor when making lightbulb purchasing choices. And as we mentioned in section III (b), lightbulbs in the U.S. are not usually sold individually. If consumer perceives certain level of failing probability from buying one LED lightbulb, then p_{LED} might increase (even double) if they have to buy two or more at a time now.

What it all comes down to is that consumer may not go through the rationalization process as proposed by our discrete choice model. Most LED and incandescent lightbulbs can be bought for less than $10, which is not a huge spending for middle-class consumers. Hence, when making decisions, consumer might not think much of future electricity savings, which would invalidate our entire framework. Our theoretical model will be robust for rational consumers who sees future electricity costs as a major factor when selecting lightbulbs; for consumers with other focuses, their preferences may be better modeled under another framework.

VI. Conclusion

This paper starts off with the observation of "the energy paradox". While many theories have been proposed to explain this phenomenon, we focus on the uncertainty factor and the U.S. residential lighting market in attempts to evaluate uncertainty's contribution to "the energy paradox". In our discrete choice model, we consider the source of uncertainty being the probability of lightbulb failing out in each period, where LED has a higher failing probability than the incandescent. After running Monte Carlo simulations to replicate consumer's decision making, we found that uncertainty can theoretically explain "the energy paradox", given that people who discount for future costs even by a slight amount (discount factor around 0.9) will overwhelmingly favor buying incandescent products over LED. We also looked at different scenarios where we reduce LED's cost level, and find that uncertain consumers, while more likely to favor LED products in general, still purchases incandescent if they are slightly impatient towards future savings.

Following section V (b), many could be done to improve the robustness of our model. To start with, engineering research could be conducted on incandescent and LED's failing mechanism to more precisely determine failing probability p_k's distribution. This would make precise of our Monte Carlo method. If empirical data is accessible, future research should also compare our theoretical model with real data to confirm our model's validity. For instance, we can choose a more reasonable upper Y cutoff bound from empirical data (the income level $\hat{Y}$ where almost all consumers already prefer LED over incandescent), making our Monte Carlo numerical results more meaningful. One way to obtain such empirical data on lightbulb market is through the Nielsen marketing database. University of Chicago's Kilts Center for Marketing hosts such dataset to selected university's tenured faculty, tenure-track faculty, Ph.D. students, and Post Doctorate students. Such marketing dataset might be suitable for empirical research if it is accessible.

Lastly, consider that lightbulb price is usually quite low, if we want to better understand theories behind "the energy paradox," we should turn our focus to a more expensive purchase. The slowly increasing fuel economy within the automobile industry could be a better market to explore: more public data is available, and the purchase itself is significantly more expensive than buying a lightbulb. When buying a vehicle, consumers are more likely to think thoroughly on all factors of the vehicle, rather than possibly making an impulsive purchase. Thus, for my next step of research on “the energy paradox,” I would look at the automobile industry, using empirical and theoretical approaches to examine theories behind “the energy paradox.”

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Table 1: Descriptive statistics for collected incandescent lightbulb cost

Brightness (Watts)	Observations	Mean	Median	Min	Max	S.D.
40	21	2.37	1.70	0.62	9.99	2.24
60	9	3.50	3.70	1.10	5.99	1.81
75	6	3.04	2.81	1.55	5.25	1.23
100	4	3.16	3.05	2.79	3.75	0.42

Notes:

1) Excluded the following extreme observations based on the sample's price histogram:
    a. 40 Watts: no exclusion.
    b. 60 Watts: any observation with per unit price higher than $6.
    c. 75 Watts: any observation with per unit price higher than $6.
    d. 100 Watts: any observation with per unit price higher than $4.
2) Prices recorded here are per unit price, which is calculated through dividing the price of a package of lightbulbs by the number of lightbulbs within.
3) "S.D." stands for standard deviation.

Sources: Target.com, Walmart.com. Data collected on March 31, 2018.

Table 2: Descriptive statistics for collected LED lightbulb cost

Brightness (Equivalent INC Watts)	Observations	Mean	Median	Min	Max	S.D.
40	17	4.56	3.92	1.24	7.90	2.05
60	29	4.76	3.77	1.24	9.00	2.66
75	7	5.83	5.60	2.49	8.48	2.14
100	2	4.62	4.62	2.74	6.50	2.65

Notes:

1) "INC" stands for incandescent lightbulbs.
2) Equivalent INC watts means using LED lightbulb to generate the equivalent amount of light as using such kind of incandescent lightbulb. Some bulbs list three levels of equivalent W_{INC}. In that case, equivalent W_{INC} is taken as the median of the three.
3) Excluded the following extreme observations based on the sample's price histogram:
    a. 40 Watts: any observation with per unit price higher than $8.
    b. 60 Watts: any observation with per unit price higher than $10.
    c. 75 Watts: any observation with per unit price higher than $10.
    d. 100 Watts: any observation with per unit price higher than $8.
4) Prices recorded here are per unit price, which is calculated through dividing the price of a package of lightbulbs by the number of lightbulbs within.
5) "S.D." stands standard deviation.

Sources: Target.com, Walmart.com. Data collected on March 31, 2018.

Table 3: Conversion between W_{INC} and W_{LED}

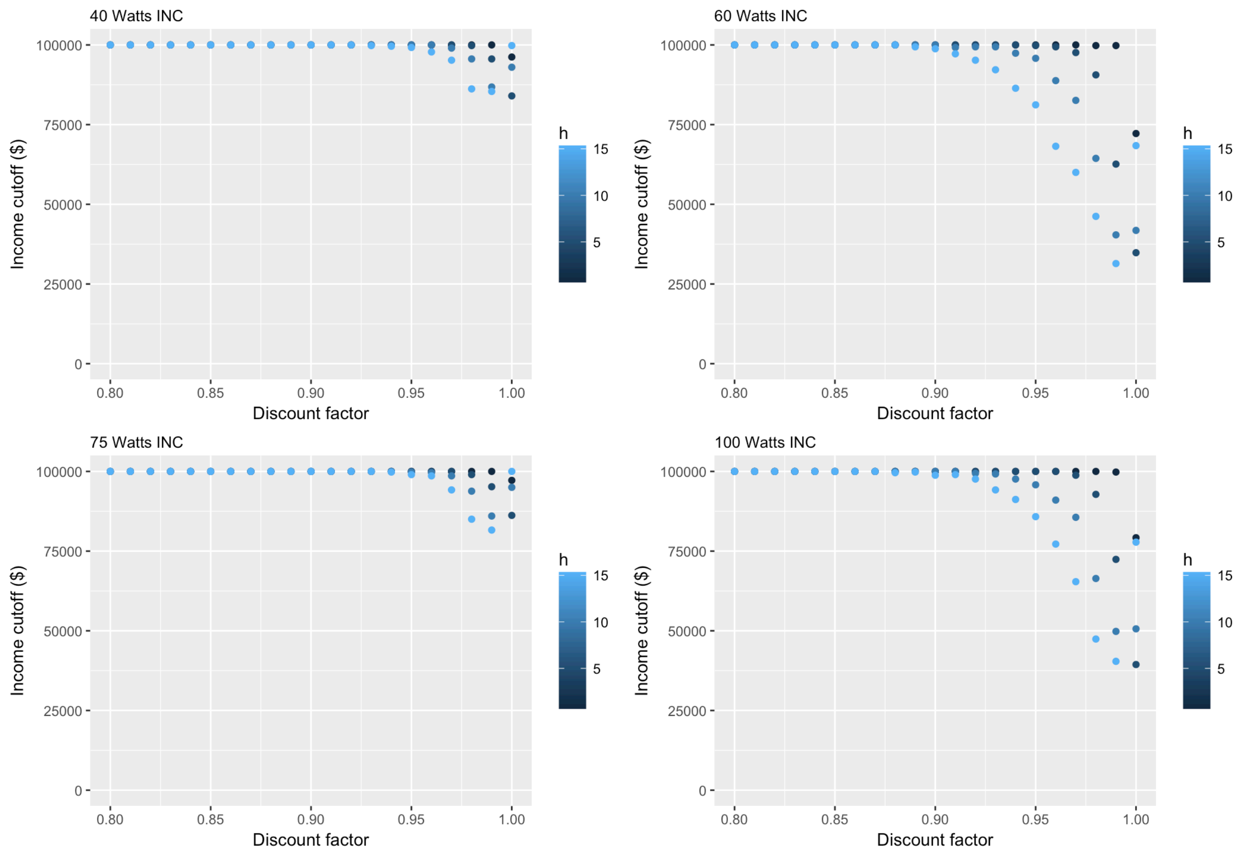
W_{INC} (Watts)	Equivalent W_{LED} (Watts)
40	6 – 7
60	8 – 13
75	12 – 15
100	16 – 17

Notes:

1) "INC" stands for incandescent lightbulbs.
2) For each row, using either incandescent or LED will generate the same amount of light. For instance, using 40 Watts incandescent lightbulb will produce same level of brightness as using a 6 to 7 Watts LED lightbulb.

Source: 1000bulbs.com, a company specialized in selling lightbulbs.

Figure 1: Effect of δ, W_{INC}, and h on Y cutoff, with C_{LED} and C_{INC} at market price level

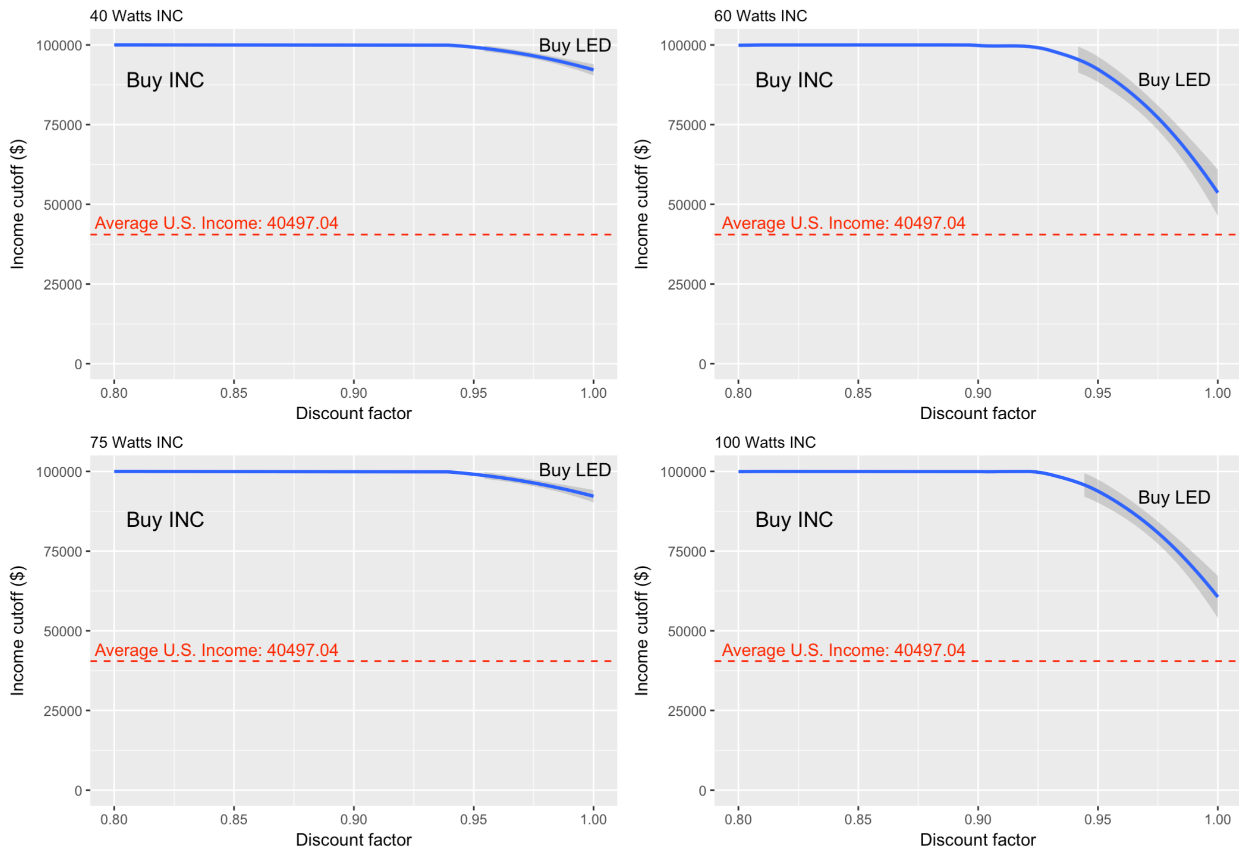


Notes:

1) "INC" stands for incandescent lightbulbs.
2) Market price means taken the cost of LED and incandescent as what we have found from the collected sample (see Table 1 and 2).
3) Points on graph represent the indifferent customer's income level (which we denote as Y cutoff points), given certain discount factor δ, level of brightness desires W_{INC}, and daily lightbulb operating hours h.
4) To interpret the Y cutoffs, we say consumers who earn an income higher than the Y cutoff prefer LED over incandescents, and consumers who earn an income below Y cutoff prefer incandescent over LED, holding δ, W_{INC}, and h fixed.

Program used: R

Figure 2: Effect of δ and W_{INC} on Y cutoff, with C_{LED} and C_{INC} taken as market price level, and h at average level



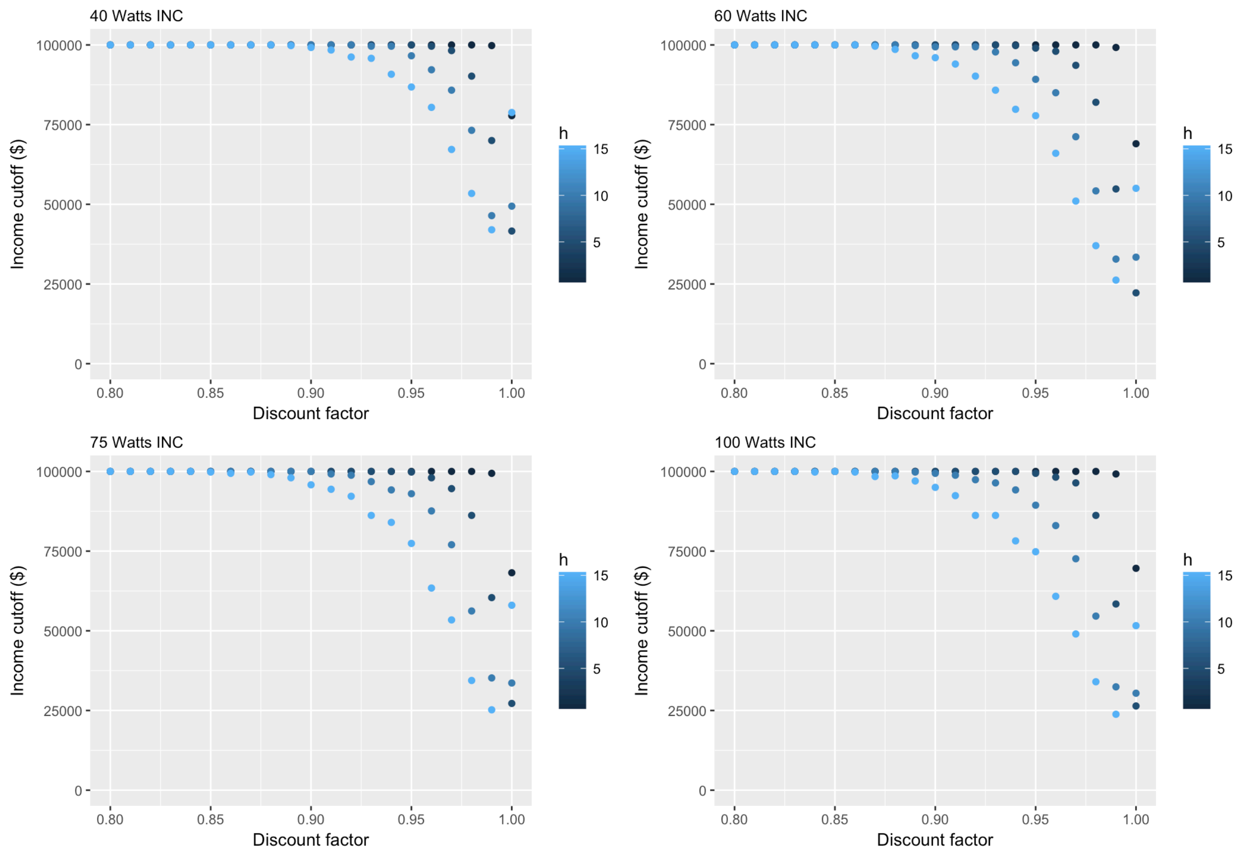
Notes:

1) "INC" stands for incandescent lightbulbs.
2) Market price means taken the cost of LED and incandescent as what we have found from the collected sample (see Table 1 and 2).
3) Blue line in each panel is reproduced from points in Figure 1. We take the average of the four daily operating hour's levels (1, 5, 10, and 15 hours), then plot the line based on the average h derived.
4) Gray band surrounding some part of the blue line is the pointwise confidence interval generated by smoothed local regression.
5) Interpretation of the blue line is the following: individuals with income higher than the blue line will prefer LED over INC, individuals with income lower than the blue line will prefer INC over LED, all while holding δ and W_{INC} fixed.
6) "Average U.S. Income" means the average yearly pre-tax income level of an U.S. individual in 2016.

Program used: R

Source of "Average U.S. Income:" Current Population Survey (IPUMS-CPS).

Figure 3: Effect of δ, W_{INC}, and h on Y cutoff, with $C_{LED} = 1 + C_{INC}$

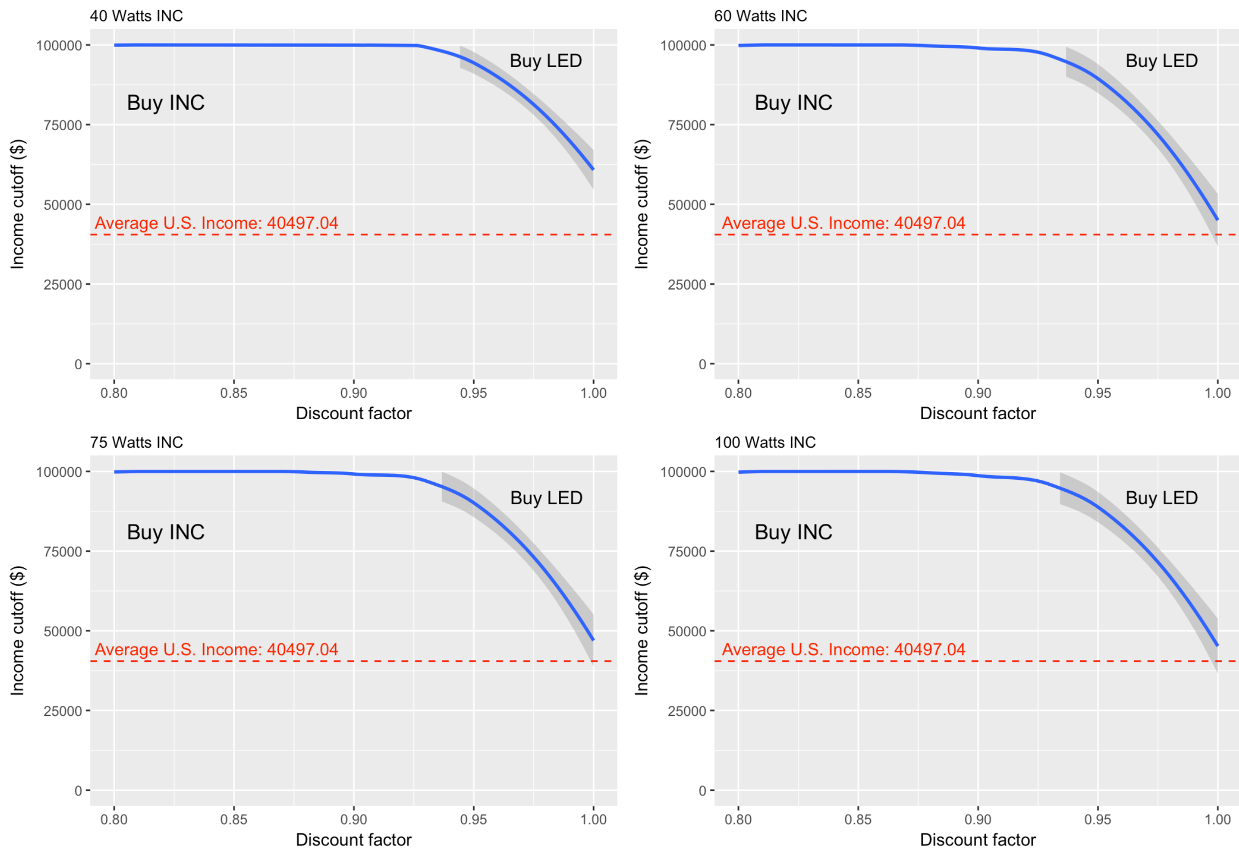


Notes:

1) "INC" stands for incandescent lightbulbs.
2) $C_{LED} = 1 + C_{INC}$ means that cost of LED is consistently one dollar higher than incandescent's, where the cost of incandescent is taken from the collected sample (see Table 1).
3) Points on graph represent the indifferent customer's income level (which we denote as Y cutoff points), given certain discount factor δ, level of brightness desires W_{INC}, and daily lightbulb operating hours h.
4) To interpret the Y cutoffs, we say consumers who earn an income higher than the Y cutoff prefer LED over incandescents, and consumers who earn an income below Y cutoff prefer incandescent over LED, holding δ, W_{INC}, and h fixed.

Program used: R

Figure 4: Effect of δ and W_{INC} on Y cutoff, with $C_{LED} = 1 + C_{INC}$, and h at average level



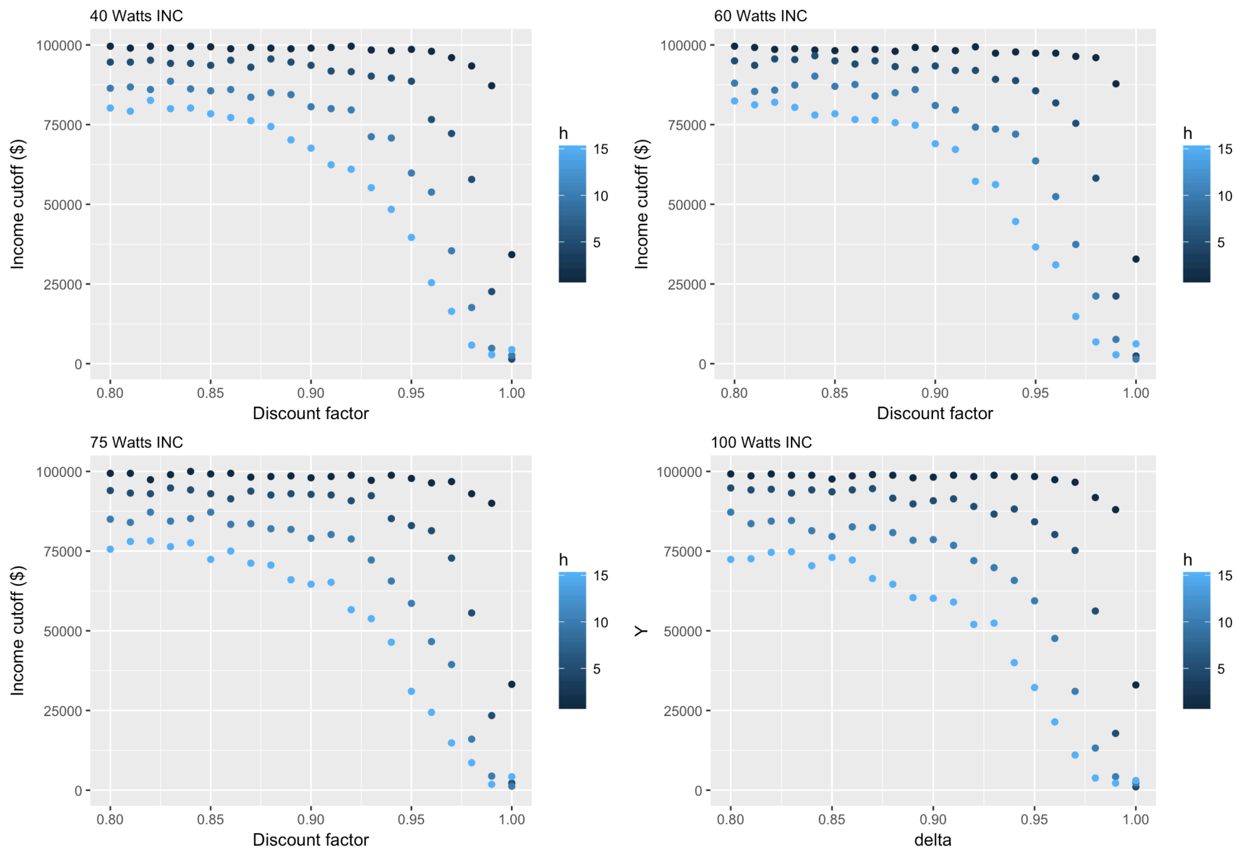
Notes:

1) "INC" stands for incandescent lightbulbs.
2) $C_{LED} = 1 + C_{INC}$ means that cost of LED is consistently one dollar higher than incandescent's, where the cost of incandescent is taken from the collected sample (see Table 1).
3) Blue line in each panel is reproduced from points in Figure 3. We take the average of the four daily operating hour's levels (1, 5, 10, and 15 hours), then plot the line based on the average h derived.
4) Gray band surrounding some part of the blue line is the pointwise confidence interval generated by smoothed local regression.
5) Interpretation of the blue line is the following: individuals with income higher than the blue line will prefer LED over INC, individuals with income lower than the blue line will prefer INC over LED, all while holding δ and W_{INC} fixed.
6) "Average U.S. Income" means the average yearly pre-tax income level of an U.S. individual in 2016.

Program used: R

Source of "Average U.S. Income:" Current Population Survey (IPUMS-CPS).

Figure 5: Effect of δ, W_{INC}, and h on Y cutoff, with $C_{LED} = C_{INC}$

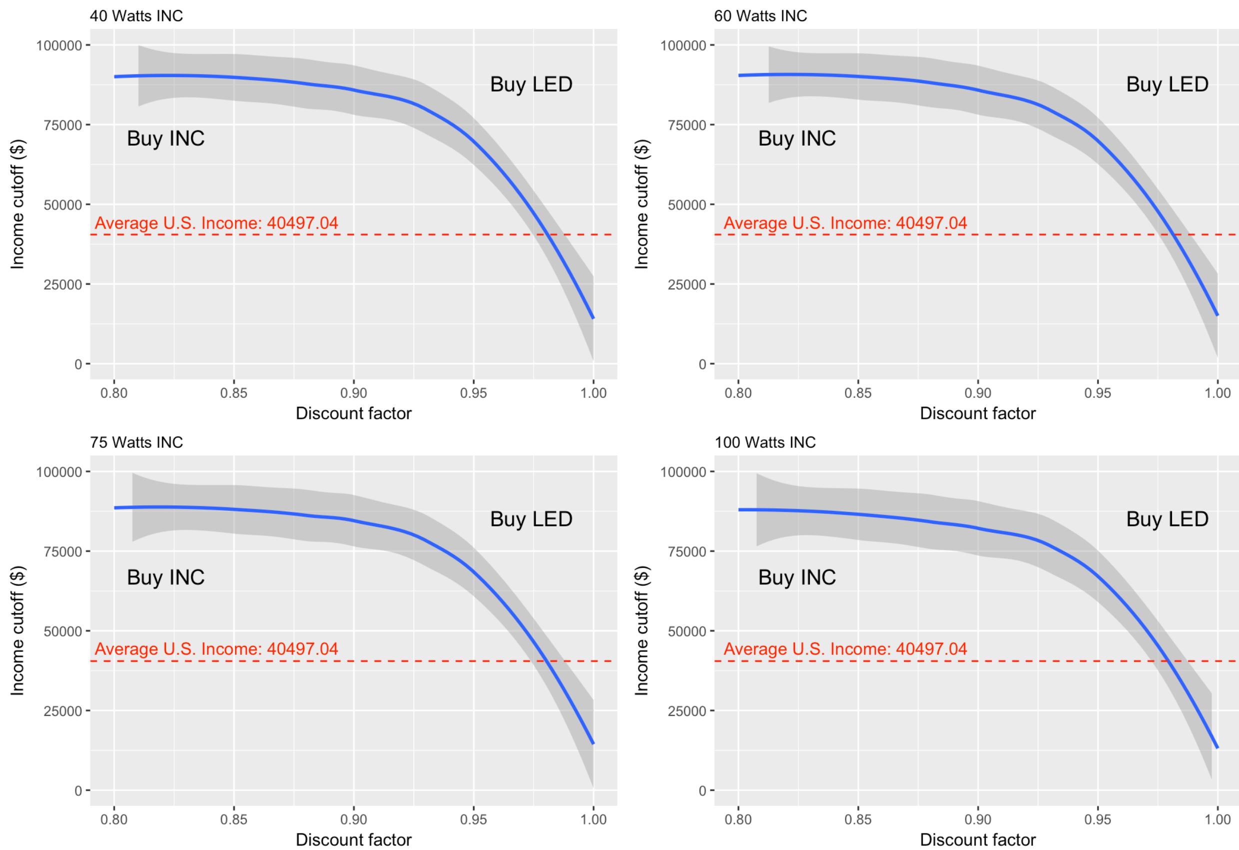


Notes:

1) "INC" stands for incandescent lightbulbs.
2) $C_{LED} = C_{INC}$ means that cost of LED is considered the same as incandescent's, where the cost of incandescent is taken from the collected sample (see Table 1).
3) Points on graph represent the indifferent customer's income level (which we denote as Y cutoff points), given certain discount factor δ, level of brightness desires W_{INC}, and daily lightbulb operating hours h.
4) To interpret the Y cutoffs, we say consumers who earn an income higher than the Y cutoff prefer LED over incandescents, and consumers who earn an income below Y cutoff prefer incandescent over LED, holding δ, W_{INC}, and h fixed.

Program used: R

Figure 6: Effect of δ and W_{INC} on Y cutoff, with $C_{LED} = C_{INC}$, and h at average level



Notes:

1) "INC" stands for incandescent lightbulbs.
2) $C_{LED} = C_{INC}$ means that cost of LED is considered the same as incandescent's, where the cost of incandescent is taken from the collected sample (see Table 1).
3) Blue line in each panel is reproduced from points in Figure 5. We take the average of the four daily operating hour's levels (1, 5, 10, and 15 hours), then plot the line based on the average h derived.
4) Gray band surrounding some part of the blue line is the pointwise confidence interval generated by smoothed local regression.
5) Interpretation of the blue line is the following: individuals with income higher than the blue line will prefer LED over INC, individuals with income lower than the blue line will prefer INC over LED, all while holding δ and W_{INC} fixed.
6) "Average U.S. Income" means the average yearly pre-tax income level of an U.S. individual in 2016.

Program used: R

Source of "Average U.S. Income:" Current Population Survey (IPUMS-CPS).