Negative Dividends: Internality Losses can Outweigh Externality Gains

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Abstract

The Energy Star certification program highlights energy efficient goods with a label. Given that it could either focus attention on the energy consumption of alternatives or provide a license to ignore the attribute, it follows that recent research highlights heterogeneity in consumers' responses to the label. This paper answers two questions implied by this heterogeneity. First, do individuals with particular characteristics respond to Energy Star certification in systematically different ways? Second, what do these differences imply about the value of the Energy Star to consumers? We present results from a stated choice experiment intended to answer these questions. Assuming an underlying random utility model and applying a mixed logit approach, we estimate utility parameters conditional on an individual's sequence of choices. Our results show that differences in consumers' responses to the Energy Star label are associated with individual characteristics. Moreover, the heterogeneity in responses implies that, though the Energy Star program lowers expected external costs associated with energy consumption, it could impose much greater internality costs on consumers. The Energy Star label may not be an appropriate non-pecuniary measure to increase consumers' attention to the energy consumption attribute of alternative goods, at least in the context of light bulb choice considered here.

Keywords: Energy Star, Energy efficiency, Internality, Stated choice, Light bulbs

JEL codes: D12, H23, Q48

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1 Introduction

With 22% of U.S. energy consumption attributable to the residential sector, changes in appliance stock could meaningfully reduce energy demand and the implied environmental externalities. However, consumers frequently choose not to purchase energy efficient alternatives that could provide them with net savings. Since Hausman (1979) showed that consumers discount future savings on energy consumption at a rate much higher than the private interest rate, a large body of literature has attempted to explain how consumers make such decisions.

Several explanations maintain that consumers are insufficiently attentive to the energy consumption attribute of alternative goods. Allcott (2011) shows that U.S. consumers do not pay much attention to fuel costs in making vehicle purchase decisions. Leard (2013) uses a separate data set to suggest that approximately 30% of consumers shopping for a new vehicle completely ignore fuel costs. In the context of appliance choice, Houde (2012) presents evidence characterizing three types of appliance consumers, two of which effectively ignore electricity cost implications. Consumers who are insufficiently attentive from a private perspective appear even more so once the socially-borne external costs of energy consumption are considered.

The Energy Star program administered by the U.S. Environmental Protection Agency (EPA) is a policy response intended to increase the salience of energy consumption. Manufacturers may label goods that meet energy consumption benchmarks with the Energy Star label. In general, such eco-labels have increased the uptake of energy efficient goods. Ward et al. (2011) estimate that customers are willing to pay an extra \$250 - \$350 for a refrigerator of a given efficiency with an Energy Star label. Nonetheless, eco-labels could either focus the consumer's attention on the energy consumption of alternatives or provide a license to ignore the attribute. This ambiguity may underpin recent findings that consumers heterogeneously respond to eco-labels such as the Energy Star. Both Houde (2012) and Shen and Saijo (2009) suggest that consumers may (1) use labels as a substitute for conventional utility optimization and ignore electricity cost and consumption data, (2) use electricity cost and consumption data to optimize choice but ignore the eco-label, or (3) use neither electricity cost and consumption data nor eco-labels in making a choice.

This heterogeneity raises two questions. First, do individuals with particular characteristics respond to Energy Star certification in systematically different ways? Second, what do these differences imply about the value of the Energy Star to consumers? This paper answers these questions using data from a stated choice experiment in which 1,550 participants made choices among alternative light bulbs. To quantify the value of the Energy Star program, we consider its impact not only on environmental externalities and consumers' experienced utility but also on consumers' internalities, as defined by by Herrnstein et al. (1993) and as applied by, e.g., Allcott, Mullainathan, and Taubinsky (2014) and Leard (2013). By definition, these internalities imply a loss of utility to the consumer. With a modeling strategy that estimates utility coefficients on energy consumption in the presence and absence of the Energy Star, we both quantify internalities and determine whether the label mitigates or exacerbates them. Moreover, we use participants' responses to non-choice questions to explain variation in internalities and the degree to which they are mitigated in the presence of the Energy Star label.

We find that, in aggregate, the Energy Star label increases consumers' valuation of savings on energy consumption. While such increases are unambiguously valuable from the perspective of externality mitigation, they only sometimes reduce internalities. In fact, the negative value of internality exacerbation is sufficiently large that it outweighs the value of internality mitigation and implies that the Energy Star label provides less value to consumers than two hypothetical instruments we consider. Though the generalizability of our work is limited, a broader message is that, in the presence of heterogeneous responses, summary statistic instruments such as the Energy Star may not be valid replacements for pecuniary ones with more homogeneous effects.

This paper contributes to a literature studying how the interactions of internalities and externalities change the choice and use of policy instruments. Our work follows Leard (2013) closely in its treatment of internalities but differs in both the context and the examination of a non-price policy instrument. Our work is also related to Allcott, Mullainathan, and Taubinsky (2014), who consider how the presence of both externalities and internalities affect energy policy-making. They suggest that pecuniary instruments to offset externalities yield a double-dividend by also reducing internalities. We provide an important nuance: the heterogenous effects of non-price instruments targeting externalities may imply a *negative dividend*.

2 Experimental and Analytical Methods

Our analysis uses compact fluorescent light bulb (CFL) choice data from a stated choice experiment. In this section, we describe our experiment and economic model of choice.

2.1 Experimental Details

Figure 1 describes the experimental procedure. We contracted with a third-party survey administration firm to recruit a nationally representative panel in the U.S. Eligible participants were U.S. residents who were at least 18 years old, owned their primary residence, and had either purchased or remodeled their residences within five years. The last criterion sought to limit participants to those who had recently made decisions about energy-consuming goods.

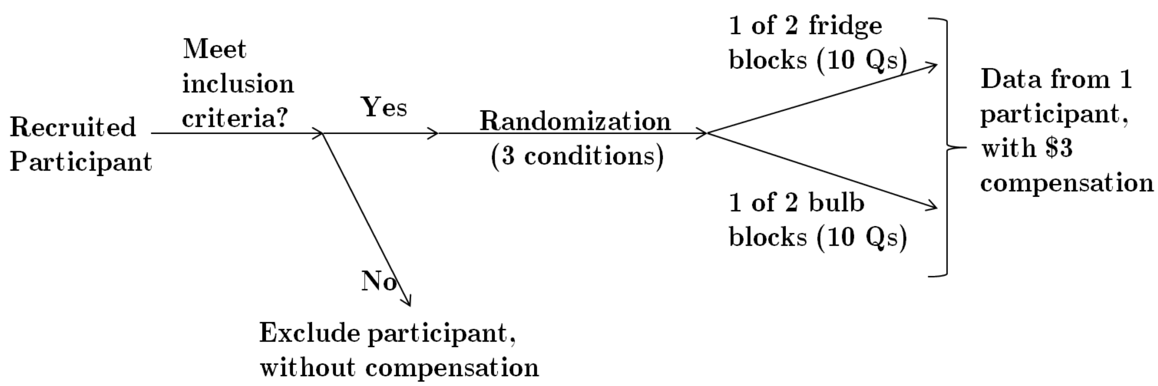
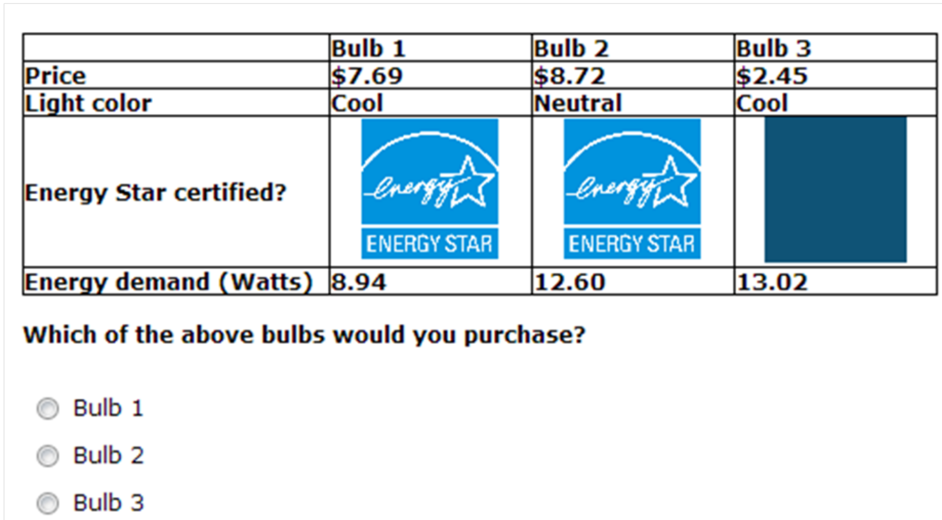


Figure 1: Overview of experimental flow

Those participants that did not meet the inclusion criteria were dismissed without compensation, while those that met them were randomized into one of three conditions. This variation was a precursor to an experiment that will be implemented separately. The three conditions differed in the denomination of the consumption information provided and in the accompanying interpretive information. Aside from adjusting the data to account for differences in error variances across conditions (see Section 3.2), these conditions are relevant only insofar as they prompt hypotheses of how the Energy Star affects individuals with different characteristics.

Participants performed a series of ten light bulb and refrigerator choice tasks. We focus on the light bulb data to isolate our message about the implications of heterogeneous responses to the Energy Star for the value of the program. For each product, twenty choice sets were organized into two blocks of ten choice sets. Following the randomization step, individuals responded to randomly assigned light bulb and refrigerator choice blocks. We generated the constituent choice sets using Ngene (ChoiceMetrics, 2012). The ranges of prices and energy consumption were such that all alternatives could have been Energy Star certified.



	Bulb 1	Bulb 2	Bulb 3
Price	$7.69	$8.72	$2.45
Light color	Cool	Neutral	Cool
Energy Star certified?	ENERGY STAR	ENERGY STAR	
Energy demand (Watts)	8.94	12.60	13.02

Which of the above bulbs would you purchase?

Bulb 1

Bulb 2

Bulb 3

Figure 2: Example bulb choice set

As Figure 2 illustrates, each participant selected one of three alternatives from each of ten choice sets. We collected 46,500 choice observations from our 1,550 participants. An alternative is characterized by three primary attributes: price, energy consumption, and the Energy Star certification. To increase the reality of the task, we also included a "service attribute"; in particular, we labeled each bulb as providing light of one of four colors.[1] Each participant received instructions about the task, information with which to interpret the attributes, and a set of assumptions to make about attributes, such as the lifetime of the light bulb.

Subsequently, each participant answered 144 demographic, psychological and financial questions intended to characterize individuals. Following the consolidation of these questions into standard metrics, our data included 35 demographic, psychological and financial variables. Two additional questions tested attentiveness to the task, and participants who answered either incorrectly were dropped without compensation. Those who successfully completed the task, including the attentiveness questions, were compensated with $3.

[1]The light color describes the warmth of the bulb's light as "warm white," "soft white," "neutral" or "cool."

2.2 Economic Model

2.2.1 Utility assumptions and choice model

We assume that participants choose the alternative yielding the highest decision utility and thereby model choices with the random utility model (RUM). We further assume that the utility from the lighting service itself is uniform across all bulbs and thus irrelevant to our modeling, which focuses on differences in utility. Formally, individual i selects good j among J alternatives in set t of T choice situations to maximize her utility, which we represent by:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \beta X_{ijt} + \varepsilon_{ijt}, \tag{1}$$

X_{ijt} is a vector of explanatory variables, including the attributes of alternatives. Equation 1 splits utility into the sum of a deterministic component, $V_{ijt} = \beta X_{ijt}$, and a random error term, ε_{ijt}. The probability, P_{ijt}, that individual i selects alternative j over k in choice set t is:

$$P_{ijt} = P(U_{ijt} > U_{ikt}) \forall k \neq j \in t \rightarrow P_{ijt} = P(\varepsilon_{ijt} - \varepsilon_{ijt} < \beta X_{ijt} - \beta X_{ikt}) \forall k \neq j \in t \tag{2}$$

A traditional assumption is that the ε_{ijt} terms are identically and independently distributed according to an extreme value type I distribution. This implies the multinomial (MNL) model in which the probability that alternative j is selected, conditional on β, is:

$$P_{ijt}(\beta) = \frac{e^{\sigma \beta X_{ijt}}}{\Sigma_{k=1}^{K} e^{\sigma \beta X_{ikt}}} \tag{3}$$

σ is a scale parameter on utility that enters the model from our assumed joint distribution of ε_{ijt}. The distribution is characterized by both location and scale parameters.

The MNL model has three limitations that we overcome by using a mixed logit (ML) estimation. ML models allow for random taste variation, unrestricted substitution patterns by permitting any specification of correlation pattern across alternatives, and a correlation in unobserved factors over choices made by the same individual (Revelt and Train, 1998). It is highly unlikely that error terms for the same individual are independent, and the mixed logit relaxes the assumption of zero off-diagonal terms in the variance-covariance matrix.

Mixed logit models "mix" MNL estimates by integrating over a joint density of parameters characterizing distributions of coefficients on particular attributes of the alternatives (Train, 2009). As such, we update the probability that alternative j is selected in choice set t to:

$$P_{ijt} = \int \frac{e^{\sigma\beta_i X_{ijt}}}{\Sigma_{k=1}^{K} e^{\sigma\beta_i X_{ikt}}} f(\beta \mid \Omega) d\beta \tag{4}$$

Equation 4 introduces a mixing distribution, $f(\beta \mid \Omega)$, over all random coefficients. The set Ω includes parameters of the distributions on random coefficients. Since an analytical solution for the likelihood function does not exist, we estimate coefficients by maximizing a simulated log likelihood function.[2] The function is defined by the product of the probabilities that individual i purchases the product actually chosen, j^*, in choice situation t:

$$SLL = \Sigma_t \Sigma_i ln P_{ij^*t} \tag{5}$$

Briefly, the procedure proceeds by (1) assuming parameter values for all elements of Ω, (2) drawing coefficient vectors, given these parameter values, (3) calculating the probability of selection of the alternative actually selected, given the coefficient vector, (4) repeating steps 1 through 3 many times, (5) averaging the probability implied by each repeat of steps 1 through 3, and (6) selecting the parameter values Ω_{SMLE} that yield the highest simulated likelihood.[3]

2.2.2 From the mixed logit to "individual-level" parameters

ML estimation thus provides us with parameters of the marginal distribution of each coefficient and the joint distribution across coefficients. Since we observe repeated choices from each participant, we can refine these estimates by conditioning on the sequence of choices, $\widetilde{y_i}$, made by participant i in the sequence of choice situations, $\widetilde{t_i}$. We accordingly assign each individual a conditional parameter distribution, rather than the sample-wide parameter distribution. Following Train (2009), upon conditioning on $\widetilde{t_i}$ and $\widetilde{y_i}$, we update the distribution of coefficients based on Ω_{SMLE}, denoted $g(\beta \mid \Omega_{SMLE})$, to $h(\beta \mid \widetilde{y_i}, \widetilde{t_i}, \Omega_{SMLE})$.

[2]Train (2009) provides additional details about simulated maximum likelihood.
[3]The subscript "SMLE" denotes simulated maximum likelihood estimator.

The distribution h re-scales the distribution g, as shown in Equation 6:

$$h(\beta \mid \widetilde{y_i}, \widetilde{t_i}, \Omega_{SMLE}) = \frac{P(\widetilde{y_i} \mid \widetilde{t_i}, \beta) g(\beta \mid \Omega_{SMLE})}{P(\widetilde{y_i} \mid \widetilde{t_i}, \Omega_{SMLE})} \tag{6}$$

Equation 6 follows from an application of Bayes' Rule and indicates that the conditional density of the coefficient vector, h, among those who choose the sequence $\widetilde{y_i}$ when choosing among $\widetilde{t_i}$ is proportional to the product of the unconditional density and the probability that $\widetilde{y_i}$ would be chosen if the coefficient vector were β. (Train, 2009)

We estimate the conditional distribution of coefficients for each individual by simulation. The simulation draws coefficient values β from the population density, $g(\beta \mid \Omega_{SMLE})$, calculates the probability of observing $\widetilde{y_i}$ given this draw, and takes the weighted average of the draws. The weights are determined by the ratio of the calculated probability for a particular draw to the sum of probabilities across all draws. (Train, 2009)

Since Ω_{SMLE} is itself estimated with sampling error, we add a second layer of simulation. This second layer draws Ω from $N(\Omega_{SMLE}, W_{SMLE})$, the estimated sampling distribution of Ω, using a Choleski decomposition of W_{SMLE} (Train, 2009). Thus, the overall simulation procedure entails multiple draws of both β and Ω. We accomplish the latter by taking 500 Halton draws and the former by taking 500 samples from the sampling distribution.

Though we refer to the resulting β_i as individual-level coefficients, they are correctly interpreted only as population coefficients, conditional on the choices made by individual i. Since the data generation process includes a fixed number of observations for each participant, the conditional mean coefficient vector, $\bar{\beta}_i$, is not a consistent estimate of β_i.

Finally, the individual-level coefficients imply individual-level willingness-to-pay (WTP) measures:

$$WTP_{il} = -\frac{\beta_{il}}{\eta_i} \tag{7}$$

The individual-level measures imply a sample-wide mean and standard deviation of the WTP.[4]

[4] We also compute parameters of the WTP distribution by performing 1,000,000 draws of the constituent mixed logit utility coefficients. Though we do not report the simulation-based WTP measures, the mean and median WTP measures are close when calculated by either approach. The standard deviations from the simulation-based method are much larger than those implied from the aggregation of the individual-level coefficients. This reflects the larger variance in the unconditional distribution relative to the conditional distribution.

2.2.3 Specifying the observable components of utility

Equation 8 details the observable components of utility:

$$V_{ij} = \eta_i \cdot p_j + \theta_i \cdot C_j + \lambda_i \cdot ES_j + \gamma_i \cdot (ES_j)(C_j) + \Upsilon_i^T Z_j \tag{8}$$

In the above model, η_i is the marginal utility of wealth, p_j is the price of product j, θ_i is the marginal utility of an additional unit of energy consumption, C_j is the energy consumption (more accurately, the power rating) of the good, λ_i is the marginal utility from the presence of the Energy Star logo. ES_j is a dummy variable equal to 1 if the product is Energy Star labeled, and γ_i is the incremental marginal utility of an additional unit of energy consumption when the product is Energy Star labeled. Finally, Υ_i is a vector of marginal utilities from the warmth of the light emitted, and Z_j is a vector of dummy variables on the warmth levels.

As Equation 8 suggests, we allow four utility coefficients to vary randomly across individuals: η_i, θ_i, λ_i, and γ_i. Since theory suggests that utility decreases in price and energy consumption, we constrain η_i and θ_i to be strictly negative by using a lognormal mixing distribution for both. Theory does not provide such guidance for the other parameters, and we use a normal mixing distribution for them. Since heterogeneity in preferences for light bulb warmth levels is uninteresting in this context, we set $\Upsilon_i = \Upsilon \; \forall \, i$. Finally, we allow the coefficient distributions to be correlated, since theory suggests, for example, that individuals with high marginal utilities of wealth may also have high marginal disutilities from energy consumption.

3 Aggregate Results

3.1 The Sample

5,919 respondents entered our experiment, and we arrived at our eventual sample of 1,550 upon removing those who either did not meet the inclusion criteria or correctly respond to the attentiveness questions. Table 1 summarizes demographic, psychological, and financial data. The lack of significant differences across conditions confirms that our sample is balanced.

Attribute	Energy Units (Cond. 1)	Dollar + Energy Units (Cond. 2)	Dollar Units (Cond. 3)	Total	Diff, (1/2)	Diff, (1/3)	Diff, (2/3)
Participants	514	507	529	1550	7	15	22
Age	50.6	49.9	50.3	50.3	0.7	0.3	0.4
% Women	49.4%	48.3%	52.2%	50.0%	1.1%	2.8%	3.9%
Household Size	2.84	2.77	2.79	2.76	0.07	0.05	0.02
Primary Earner, Wage Share	78.4	79.8	80.2	79.4	1.4	1.8	0.4
Hyperbolic Discount Rate	0.027	0.031	0.022	0.027	0.004	0.005	0.009
Exponential Discount Rate	0.021	0.023	0.017	0.020	0.002	0.004	0.006
CRT Score	0.72	0.79	0.74	0.75	0.07	0.02	0.05
Numeracy (Number Correct)	10.34	10.26	10.21	10.27	0.08	0.13	0.05
Household Income (Median)	$60 - 80K	$60 - 80K	$60 - 80K	$60 - 80K	–	–	–
Socio-economic Status (Median)	5	5	5	5	–	–	–
Past fridge buys (Median)	2	2	2	2	–	–	–
NEP	50.7	51.3	50.9	51.0	0.6	0.2	0.4
PANAS-Negative	18.7	17.9	17.8	18.2	0.8	0.9	0.1
PANAS-Positive	33.4	32.6	32.5	32.8	0.8	0.9	0.1
Big Five-Extraversion	8.46	8.08	8.24	8.26	0.22*	0.38	0.16
Big Five-Agreeable	10.49	10.47	10.51	10.49	0.02	0.02	0.04
Big Five-Conscientious	11.14	11.42	11.31	11.29	0.28	0.17	0.11
Big Five-Emotion Stability	10.16	10.14	10.12	10.14	0.02	0.04	0.02
Big Five-Openness to Exp.	9.82	9.91	9.80	9.84	0.09	0.02	0.11
Future Self-Similarity	4.88	4.94	4.94	4.92	0.06	0.06	0.00
Environmental Efficacy	14.76	14.70	14.46	14.64	0.06	0.30	0.24
Primary Financial DM	0.53	0.52	0.56	0.54	0.01	0.03	0.04
Primary Appliance DM	0.45	0.44	0.48	0.46	0.01	0.03	0.04
% of new 10K to Equities	25.72	26.73	26.70	26.39	1.01	0.98	0.03
% of Assets in Equities	32.47	32.26	31.27	31.99	0.21	1.20	0.99

Table 1: Overview of demographic, psychological and financial metrics across the sample. Significant differences at the 0.05 significance label are marked by an asterisk.

3.2 Estimation Details

Three comments about our estimation procedure clarify the interpretation of the coefficients. First, since the different units of consumption are linearly related, we use a singly denominated vector for estimation. Second, we use cluster robust variance estimators (CRVE), with observations clustered at the individual level. This allows for heterogeneity in the error structure across individuals and for an arbitrary autocorrelation structure in the errors across choice situations faced by the same individual (Wooldridge, 2010). Finally, we relax the assumption that the scale parameter in Equation 3 equals one. This assumption generally allows one to estimate β even though it is not separately identified from σ by the data. Since we combine data from three experimental conditions, we need to ensure that our estimate of β is not influenced by differences in the error variance across conditions. To adjust for possible differences, we follow methods developed by Swait and Louviere (1993). The results we present use condition-specific scale parameters, but they do not change appreciably if we reset them to equal 1.

3.3 Mixed Logit Coefficient Estimates

Table 2 presents the results of our mixed logit estimation, and the means of the coefficient distributions in Column 2 imply that the signs on price and consumption are as expected.[5] Since the ML estimates follow from a model with dummy terms on three of the four warmth levels, the outside option is a bulb of the remaining warmth level, of average price and consumption, and without Energy Star certification. Coefficients should thus be interpreted as conditional on bulb purchase. The baseline bulb can be of any of the four warmth levels, as the coefficients on price, consumption, Energy Star, and the interaction term average over all warmth levels. Column 3 provides the means from the average of conditional (individual-level) coefficients.[6] The agreement between Columns 2 and 3 provides a check that the model is correctly specified and accurately estimated (Allenby and Rossi, 1998; Train, 2009).[7]

[5] The notion of an 'expected sign' is ambiguous for bulb warmth levels, for the Energy Star label, and for the interaction between the Energy Star and consumption level. The positive coefficient on the Energy Star logo is expected to the extent that we assume consumers interpret this as some indicator of quality. We use the Stata 'mixlogit' command written by Hole (2007) for our estimation.

[6] We modify Hole's 'mixlbeta' command to estimate individual-level means and variance-covariance matrices.

[7] The mean coefficients on price and consumption are parameters of the lognormal distribution; the corresponding parameters of the normal distribution are -1.257 and -0.728, respectively.

Attribute	Mean	Mean (IL)	Variance	WTP, Mean	WTP, Med.	WTP, SD
Price	-0.684 (0.045)	-1.277	1.825 (0.129)	–	–	–
Energy Star	1.839 (0.093)	1.837	2.403 (0.229)	$4.97	$2.36	$6.46
Consumption	-1.056 (0.061)	-0.734	1.48 (0.149)	-$1.23	-$0.71	$1.65
ES*Cons.	-0.126 (0.026)	-0.126	0.019 (0.006)	-$0.15	-$0.13	$0.31
Soft white	0.186 (0.041)	–	–	$0.51	$0.35	$0.48
Neutral	-0.189 (0.054)	–	–	-$0.51	-$0.35	$0.49
Cool	-0.743 (0.060)	–	–	-$2.02	-$1.39	$1.93
LogLik	-11914.764					
Obs.	46,500					
Correctly Predicted (%)	60.2					

Table 2: Estimated ML parameters for bulb choice. Column 2 lists the mean of the coefficient distributions. Column 3 provides the average of conditional (individual-level) coefficients. Column 4 shares the estimated variance of the coefficient distributions. Columns 5 through 7 list summary statistics on WTP measures. Numbers in parentheses are standard errors.

The significant variance terms in the fourth column validate our decision to model these coefficients as random. By considering this heterogeneity, the ML model outperforms the MNL in correctly predicting 60.2% of choices relative to the latter's 51.6%.[8]

Our aggregate measures imply that participants express a positive WTP for Energy Star certification and that certification decreases the marginal utility from a 1W higher power rating. To put the WTP for the Energy Star label in context, the mean price of bulbs in the study was $5.56. In our upcoming discussion, we will refer interchangeably to the effect of the Energy Star label on the marginal disutility of a 1W higher power rating and on the marginal utility of energy consumption savings implied. If the Energy Star label increases the former, as on aggregate, it also increases the latter.

Finding 1 summarizes our findings from the ML model:

Finding 1: *ML estimates confirm heterogeneity in the coefficients. In aggregate, the Energy Star increases consumers' marginal utility from savings on energy consumption.*

[8]For individual i and choice set t, the model correctly predicts choice if it assigns the highest probability of selection to j^*, the alternative actually selected.

4 The Heterogeneous Impacts of the Energy Star

The significant variance of the Energy Star and Consumption interaction term implies that the Energy Star could either increase or decrease a participant's marginal utility coefficient on savings from energy consumption. Here, we explore the implications of such heterogeneity.

4.1 Internalities and Mitigation

To evaluate whether the Energy Star provides value or harms a particular individual, we determine whether its effect is to shift her marginal utility coefficient closer to a rational benchmark. We set the rational willingness-to-pay, WTP^R, equal to the present value of savings associated with a 1W lower power rating. The calculation assumes an electricity price of \$0.1147/kWh and that a bulb is used 3 hours daily for eight years, as shared with participants:[9]

$$WTP^R = \Sigma_{t=1}^{T=8} \frac{Savings_t}{(1+r)^t} \tag{9}$$

In Equation 9, r is the temporal discount rate. We use an individual-level discount rate elicited in the experiment and designed by Kirby and Marakovic (1996); we also report results stemming from a common 6% discount rate. Since WTP^R excludes any disutility from the environmental costs of consumption, it should be interpreted as a "selfishly" rational measure. These costs should not markedly change WTP^R. Even if all electricity consumed were generated from coal, the allocation of the external costs of \$0.11/kWh uniformly over a small population of 100,000 implies a cost of one-ten thousandth of a cent per kWh per person.[10]

The estimated marginal utility of wealth, η_i, points to a benchmark utility coefficient on energy consumption, θ_i^R, that would imply the individual would be willing to pay WTP^R:

$$\theta_i^R = WTP^R \cdot \eta_i \tag{10}$$

We define the *internality*, int_i, as the difference between θ_i^R and the estimated coefficient, θ_i:

$$int_i = \theta_i^R - \theta_i \tag{11}$$

[9] This assumes that the rational consumer holds an expectation that electricity rates will remain constant.
[10] This estimated cost is the median from Sundqvist (2004) adjusted from 1998 to 2013 dollars.

Though the utility coefficients on energy consumption are constrained to be negative, we discuss the negative of the coefficients for ease of interpretation. Thus, individuals with positive internalities undervalue savings on energy consumption, and those with negative internalities overvalue them. We discuss γ_i similarly; the higher it is, the greater is the impact of the Energy Star in increasing an individual's valuation of savings on energy consumption.

The *mitigation*, mit_i, performed by the Energy Star logo is the degree to which it decreases the internality. We define mit_i as the ratio of the Energy Star*Consumption term, γ_i, to int_i:

$$mit_i = \frac{\gamma_i}{int_i} = \frac{\gamma_i}{(\theta_i^R - \theta_i)} \tag{12}$$

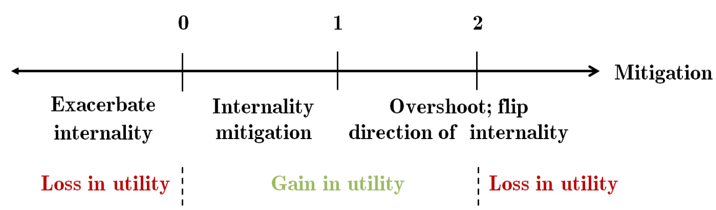


Figure 3: The mitigation scale includes three areas: (1) internality exacerbation, (2) internality mitigation, and (3) an overshoot in mitigation. The first and second areas imply only utility losses and gains, respectively. In the third, utility gains occur only if $1 < mit_i < 2$.

As Figure 3 shows, mit_i links the effect of the Energy Star on internalities to changes in consumer utility. When $mit_i < 0$, the Energy Star impacts θ_i in the direction opposite of that needed to erase the internality and yields a loss in utility. The Energy Star delivers the largest utility gain when it just closes the internality, or when $mit_i = 1$. When $0 < mit_i < 1$, the Energy Star partially closes the internality and increases consumer utility. When $mit_i > 1$, the Energy Star overcompensates; the sign of the internality flips, and a gap between θ_i^R and $\theta_i + \gamma_i$ remains. If $1 < mit_i < 2$, the magnitude of the internality decreases, and consumer utility increases. However, if $mit_i > 2$, a larger oppositely-signed internality implies a loss in utility. Before Section 5, we consider only internality changes in discussing consumer utility.

Figure 4 plots int_i and mit_i from our data.[11] In isolation, the means suggest the Energy Star is working as intended. The mean internality is greater than zero, and the mean mitigation indicates the Energy Star shifts individuals' utility coefficients toward the rational level.

[11] Figure 4 is truncated at ±5. The internalities range from -6.6 to 10.4 and mitigation from -66.4 to 86.9.

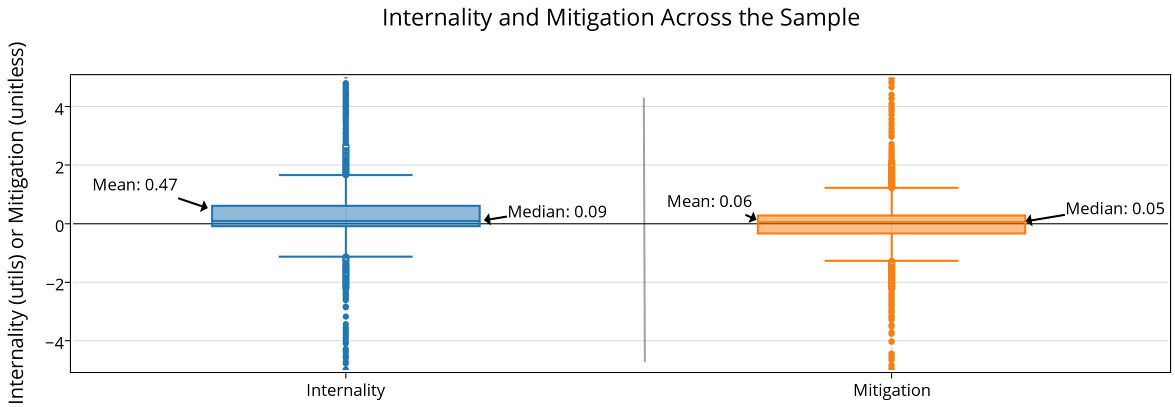


Figure 4: The observed internalities and mitigation imply substantial heterogeneity both in response to consumption information and the Energy Star label. The plot is truncated at ± 5.

Figure 5 categorizes the utility ramifications of the Energy Star. We group participants into four groups defined by the signs of int_i and γ_i. In our sample, 60, 146, 829, and 515 participants are in Groups A, B, C, and D, respectively.[12] These group counts motivate two sets of questions about individual-level characteristics. Since 85% of individuals are in Groups C and D, we ask in Section 4.2 whether individuals with certain characteristics are prone to positive or negative internalities. Section 4.3 subsequently asks if the Energy Star more often exerts an influence on θ_i in the correct direction for participants with certain individual-level characteristics.

4.2 Internalities and Individual-level Characteristics

Since the Energy Star increases the utility coefficient on energy consumption for 85% of the sample, we can derive clues about who benefits from the Energy Star program by identifying the personal traits associated with the direction of internalities. We use a binomial logit model to describe the probability that an individual has a negative internality; the Energy Star label generally yields negative benefits to these individuals. Formally, we model:

$$P(int_i < 0 \mid O_i) = \frac{e^{\xi O_i}}{1 + e^{\xi O_i}} \tag{13}$$

O_i is a matrix of observed co-variates, and ξ are the corresponding coefficients. Besides the

[12] These counts are based on rational benchmarks defined by individual-level discount rates. If we use a common 6% discount rate, the group counts are 41, 165, 869, and 475, respectively.

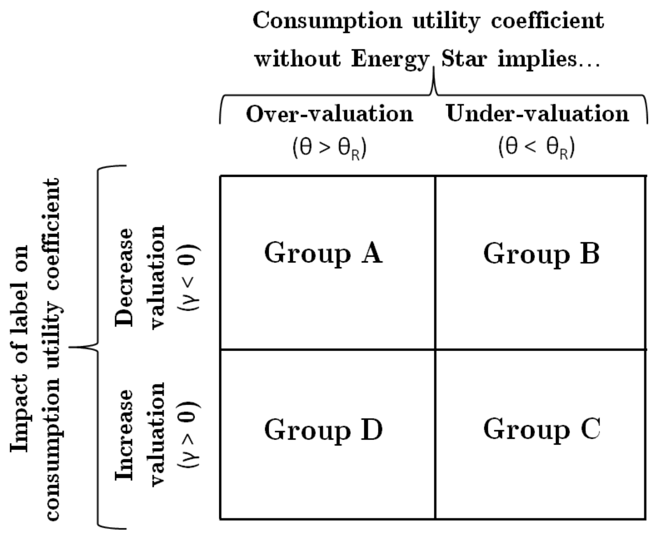


Figure 5: Participants are binned into four groups defined by int_i and γ_i.

demographic factors of age, gender, household income, and education that serve as controls, O_i includes three hypothesized drivers of internalities.[13]

The first driver relates to environmental concern, since those with high environmental concern may display nearly lexicographic preferences on energy consumption. We measure environmental concern by the New Ecological Paradigm (NEP) metric (Dunlap et al., 2000) and hypothesize that it is positively associated with the probability of negative internalities ($\xi_{NEP} > 0$). We also include an interaction between NEP and positive affect, as measured by the so-called PANAS psychometric. Since positive affect may induce risk-taking on energy consumption among low NEP individuals or prompt a high focus on the attribute among high NEP individuals, we hypothesize that $\xi_{Affect(PANAS)*NEP} > 0$ (Kuhnen and Knutson, 2011).

The second concerns cognitive ability. Condition 1 provided energy consumption data only in terms of energy units, and we hypothesize that higher numeracy moderates under- or over-valuation of energy consumption savings that may arise in this condition ($\xi_{Cond.1*Numeracy} \neq 0$). Similarly, Condition 3 provided energy consumption data in both energy and dollar units. We hypothesize that higher cognitive reflection would moderate under- or over-valuation that may arise in this condition and therefore that $\xi_{Cond.3*CRT} \neq 0$ (Frederick, 2005).

[13] Our hypotheses exclude variables with insufficient variation in the sample, such as liquidity constraints and financial and appliance decision-making capacity. We also exclude variables, such as cash and the cognitive reflective test score, that are highly correlated with others. Finally, we do not consider those without reasonable links to internalities, such as household size and four of the Big Five personality attributes.

The final includes financial drivers. In particular, we hypothesize that low asset holdings predict the direction of internalities. However, we expect two impacts, with one associated with low future self-similarity (FSS) and the other with high FSS (Ersner-Hershfield et al., 2009). For the former, we expect low asset holdings to heighten attention on price at the expense of consumption; for the latter, we expect low asset holdings to increase focus on the implications of long-run costs. Accordingly, we hypothesize that $\xi_{Assets*FSS} < 0$. In addition, since the present value of consumption savings increases with the discount rate, we expect the discount rate to be negatively associated with over-valuation; this hypothesis applies only to the situation in which we assume a constant 6% discount rate across all individuals.

Table 3 lists our estimates.[14] We infer that NEP is significantly associated with negative internalities and numeracy with positive internalities.[15] The latter effect is more general than we hypothesized, and we summarize our findings in Finding 2:[16]

Finding 2: *High-NEP individuals are more likely to have a negative internality, while those with high numeracy are more likely to have a positive internality.*

4.3 Mitigation and Individual-level Characteristics

Finding 2 implies that individual utilities would be uniformly improved by the Energy Star only if it were able to exert different influences throughout the population. However, the mitigation measure is between 0 and 2 for only 53% of the sample.[17] To examine if the Energy Star offsets the internalities of highly numerate and high NEP individuals in the "correct" direction, we fit a multinomial logistic regression for membership in Groups A, B, C, and D. If the label accomplishes the former, we would observe a significant coefficient on numeracy for membership in Group C. Members of this group have $\gamma > 0$ and under-value energy consumption savings. If it accomplishes the latter, we would observe a significant coefficient on NEP for membership in Group A. These participants have $\gamma < 0$ and over-value energy consumption savings.

[14] We perform the estimation on a sample that excludes 11 individuals who did not answer the question informing our FSS measure.

[15] While we have modeled the probability of $int_i < 0$, the signs of coefficients would reverse upon modeling the probability of $int_i > 0$.

[16] We refrain from inferring economic significance from the rejection of nulls for two of the other four hypotheses since the rejection is sensitive to discount rate assumptions.

[17] The proportion is the same regardless of the discount rate assumption.

Attribute	**Individual-level**	**6% discount rate**
Intercept	0.846 (0.223)	0.853 (0.224)
Age	-0.004 (0.004)	0.003 (0.004)
Gender	-0.145 (0.115)	0.042 (0.111)
HH Income	0.045 (0.027)	0.062 (0.027)
Education(2)	0.039 (0.179)	0.106 (0.175)
Education(3)	-0.080 (0.146)	-0.048 (0.141)
Education(4)	-0.044 (0.173)	0.209 (0.168)
NEP	0.022 (0.006)	0.025 (0.006)
PANASPos*NEP	0.002 (0.001)	0.001 (0.001)
Discount rate	–	-0.811 (0.702)
Assets*FSS	-0.011 (0.007)	-0.008 (0.007)
Numeracy*Cond1	-0.090 (0.023)	-0.074 (0.023)
Numeracy*Cond2	-0.098 (0.023)	-0.070 (0.023)
Numeracy*Cond3	-0.180 (0.025)	-0.156 (0.024)
CRT*Cond1	-0.227 (0.113)	-0.189 (0.108)
CRT*Cond2	-0.017 (0.098)	-0.108 (0.096)
CRT*Cond3	0.007 (0.124)	-0.053 (0.115)
AIC	1932.2	2029.3
LogLik (df)	-950.08 (16)	-997.65 (17)
Residual deviance (df)	1900.2 (1523)	1995.3 (1522)
N	1539	1539
Correctly Predicted (%)	9.94	24.4

Table 3: Estimated coefficients (log-odds) in a logit model of consumption savings overvaluation. Entries in parentheses are standard errors, except where otherwise indicated.

The multinomial logit model estimates the probability that individual i is a member of group g. Equation 14 expresses the probability of group membership:

$$P_{ig}(\kappa) = \frac{e^{\kappa_g K_i}}{\Sigma_{g'=1}^{G=3} e^{\kappa_{g'} K_i}} \tag{14}$$

The vector κ_g includes coefficients on attributes K_i for membership in group g by individual i.

Table 4 provides our estimates of κ on the co-variates K_i from Table 3.[18] We highlight that high-NEP and high numeracy individuals are significantly more likely to be members of Groups D and C, respectively.[19] The implication is that while the Energy Star label is more likely to affect the positive internalities of highly numerate types in the right direction, it is more likely to exacerbate the negative internalities of high-NEP types. The relative value of each action depends on the marginal utilities of wealth of these individuals, and Section 5 determines whether the value of internality closures offsets that of internality exacerbation. Nonetheless, given that $\gamma_i > 0$ for 85% of individuals though only 63% have a positive internality, we can by now develop a strong intuition for the negative value of the Energy Star program.

Finding 3 summarizes our findings on the direction of Energy Star effects.

Finding 3: *Energy Star effects imply a mitigation measure in the "target" zone of 0 – 2 in 53% of cases. The Energy Star preferentially mitigates positive internalities among highly numerate individuals and exacerbates negative internalities among high-NEP individuals.*

5 The Value of the Energy Star to Consumers

5.1 Valuation Methodology

The Energy Star yields changes in internalities, external costs of electricity generation, and experienced utility that must be valued. The Energy Star affects experienced utility because it impacts the probability that individual i selects bulb j and therefore the expected utility from bulb purchase. Equation 15 captures the three effects:

$$Value_{ES} = (CS^{exp}_{ES} - CS^{exp}_{NES}) - (CS^{int}_{ES} - CS^{int}_{NES}) - (ECE_{ES} - ECE_{NES}) \tag{15}$$

In the expression above, CS^{int} represents the internality consumer surplus, CS^{exp} the experienced utility from bulb purchase, ES the setting in which the Energy Star exists, NES that

[18] We base our selection of co-variates on this table because the group membership model requires hypotheses about the co-variates relevant to over- and under-valuation. Economic and psychological theory do not provide additional guidance on the co-variates relevant to the direction of γ.

[19] In addition, income is significantly associated with membership in Group A.

Attribute	Individual-level			6% discount rate		
	Group B	Group C	Group D	Group B	Group C	Group D
Intercept	0.627 (0.347)	2.692 (0.299)	2.253 (0.303)	0.709 (0.337)	2.676 (0.284)	2.478 (0.285)
Age	0.008 (0.012)	0.026 (0.011)	0.021 (0.011)	-0.010 (0.011)	0.012 (0.009)	0.012 (0.009)
Gender	0.580 (0.325)	0.248 (0.287)	0.158 (0.291)	0.026 (0.300)	-0.219 (0.248)	-0.180 (0.249)
HH Income	-0.114 (0.078)	-0.216 (0.070)	-0.175 (0.070)	-0.135 (0.072)	-0.220 (0.060)	-0.170 (0.060)
Education (2)	0.393 (0.633)	0.404 (0.571)	0.517 (0.576)	-0.167 (0.550)	-0.018 (0.458)	0.115 (0.459)
Education (3)	0.049 (0.419)	-0.019 (0.366)	-0.106 (0.372)	-0.521 (0.395)	-0.344 (0.323)	-0.480 (0.325)
Education (4)	0.380 (0.478)	-0.112 (0.427)	-0.020 (0.433)	-0.074 (0.444)	-0.537 (0.377)	-0.236 (0.375)
NEP	0.004 (0.018)	0.007 (0.015)	0.031 (0.016)	0.001 (0.016)	0.001 (0.013)	0.028 (0.014)
Discount rate	–	–	–	0.128 (1.570)	-0.233 (1.312)	-0.916 (1.309)
Numeracy	0.030 (0.050)	0.181 (0.045)	0.039 (0.045)	0.054 (0.049)	0.178 (0.040)	0.071 (0.039)
CRT	0.256 (0.192)	0.184 (0.173)	0.143 (0.177)	0.362 (0.179)	0.252 (0.154)	0.180 (0.156)
PANASPos*NEP	-0.001 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.000 (0.002)	0.002 (0.002)
Assets*FSS	-0.001 (0.020)	0.005 (0.018)	-0.009 (0.018)	0.001 (0.019)	0.004 (0.016)	-0.006 (0.016)
N	1539	–	–	1539	–	–
AIC	3174.483	–	–	3181.745	–	–
LogLik (df)	-1537.741 (36)	–	–	-1590.873 (39)	–	–
Residual deviance (df)	3075.483 (1503)	–	–	3181.745 (1500)	–	–
Correctly Predicted (%)	56.0	–	–	50.1	–	–

Table 4: Estimated log-odds of group membership in the bulb data. Group A is the base level. Our inclusion of the FSS variable requires a removal of 11 subjects who did not answer a question informing our measure of future self-continuity. Entries in parentheses are standard errors, except where otherwise indicated.

in which it does not, and ECE the external costs of electricity. Changes in CS^{int} and ECE enter negatively because consumers benefit from smaller internalities and external costs.

Our valuation reflects several assumptions. Our use of a traditional public economics valuation approach assumes that consumers incorrectly consider only the energy consumption attribute. Moreover, notwithstanding the findings by Houde (2013) that firms respond strategically to the Energy Star certification, we assume a competitive supply side that sells the same products with and without the Energy Star. We further assume that firms do not modify the prices of their products in response to consumers' valuation of the Energy Star label itself.

Following Small and Rosen (1981) and Leard (2013), Equation 15 must be evaluated in expectation, since we estimate the probability with which consumer i would choose alternative j. To evaluate the expected change in value, we apply the individual-level utility coefficients to simulate consumer choice in both the absence and presence of the Energy Star. We use a choice set containing CFLs available for purchase in a large national retailer in early 2014.[20] The simulation yields choice probabilities in the absence and presence of the Energy Star program.

With those probabilities, we compute the expected change in internality consumer surplus:

$$\mathbb{E}[\Delta CS^{int}] = \Sigma_i \Sigma_j P_{ij}^{ES} \frac{I_{ij}^{ES}}{\eta_i} - P_{ij}^{NES} \frac{I_{ij}^{NES}}{\eta_i} \tag{16}$$

P_{ij}^{ES} and P_{ij}^{NES} are the simulated probabilities that participant i selects alternative j when the Energy Star program exists and when it does not. I_{ij} measures the internality utility:

$$I_{ij}^{ES} = \eta_i \cdot (WTP_i^R - \frac{\theta_i + \gamma_i}{\eta_i}) \cdot W_j \tag{17}$$

$$I_{ij}^{NES} = \eta_i \cdot (WTP_i^R - \frac{\theta_i}{\eta_i}) \cdot W_j \tag{18}$$

Note that since it measures a deviation from a rational benchmark, the internality utility is properly interpreted as a disutility; the consumer benefits from decreases in internality utility.

In Equations 17 and 18, the power rating W_j scales the difference between the rational willingness-to-pay for a 1W reduction in power and the econometrically estimated willingness-to-pay. The left η_i term translates this difference into units of utility. The terms preceding W_j in Equations 17 and 18 are equal to the pre- and post-Energy Star internality levels, respectively. Equation 16 derives a surplus measure by translating the internality utility into dollar terms.

Equation 19 computes the expected change in the external costs of electricity:

$$\mathbb{E}[\Delta ECE] = \Sigma_i \Sigma_j (P_{ij}^{ES} - P_{ij}^{NES}) \cdot EC_j \tag{19}$$

EC_j is the external cost of the expected kilowatt hours of electricity consumed by product j.

[20] We exclude certain bulbs with warmth levels beyond those considered in the choice experiment.

We derive the latter by calculating the electricity consumed by a 1W bulb operating for 3 hours daily for 8 years and scaling this by both the power rating of bulb j and the external cost per kWh of electricity generation. We discount future costs using a 6% social discount rate, r_s:[21]

$$EC_j = \Sigma_{t=1}^{T=8} \frac{\frac{W_j(T*3*365)}{1000} ED}{(1+r_s)^t} \tag{20}$$

We assume that ED, the environmental damage per kWh of electricity generated, equals \$0.068/kWh. This is a weighted average of environmental damage estimates for electricity derived from coal, oil, natural gas, nuclear, hydro, wind, and solar sources, with weights determined by the share of generation from each source. We scale the damage estimates from 1998 dollars to 2013 dollars using the U.S. BLS Inflation Calculator. For each source, we use the median level of environmental damages reviewed by Sundqvist (2004) and share of electricity generation from the U.S. Energy Information Agency (2013).[22]

Finally, we calculate the expected change in experienced consumer surplus:

$$\mathbb{E}[\Delta CS^{exp}] = \Sigma_i \Sigma_j P_{ij}^{ES} \frac{H_{ij}^{ES}}{\eta_i} - P_{ij}^{NES} \frac{H_{ij}^{NES}}{\eta_i} \tag{21}$$

In both cases, we define H_{ij} as:

$$H_{ij} = \eta_i \cdot p_j + \theta_i \cdot C_j + \beta_i^T X_j \tag{22}$$

Comparing Equations 22 and 8, we note that the experienced utility calculation does not include the impact of either the Energy Star or the interaction between it and consumption. We remove the effect of the label from Equation 22 because we believe it does not contribute to experienced utility.[23] We do not include the effect of the interaction term because its impact is already captured in the valuation of the change in internality consumer surplus. Moreover, Equation 22 does not include utility from the lighting services themselves, given our earlier

[21] Since the marginal costs of greenhouse gas emissions reflect the aggregate stock of emissions, they increase at the rate of inflation. Strictly speaking, we should not discount these costs by the social discount rate. However, we use an aggregated measure of external costs; though a disaggregation would refine our valuation estimates, it does not add to the central point of the paper.

[22] In particular, we use data from a table of Net Generation by Energy Source. We allot generation from "petroleum liquids" to oil and remove the small amount of generation from petcoke, "other gas" and biomass.

[23] This is consistent with Houde (2013), and we echo his assertion that this is in reality open to debate.

assumption that this utility is constant across all candidate goods.

5.2 Could Other Instruments Deliver Higher Value?

5.2.1 An alternative label

We consider a hypothetical label that targets only those with high numeracy. Our assumption is that the label exactly offsets the median value of the internality at a given level of numeracy. The specificity of this hypothetical label could limit the mismatch between the direction of internalities and that of the effect of the Energy Star. The valuation method differs only slightly from that used in Section 5.1. First, we measure the effect of the instrument through a term, γ_i^{Hypo}, where *Hypo* designates the hypothetical label. We set γ_i^{Hypo} equal to the product of the median value of the internality for those with the numeracy of participant i and the marginal utility of wealth of participant i. Formally, $\gamma_i^{Hypo} = \eta_i \cdot median(\frac{(\theta_z^R - \theta_z)}{\eta_z})$ for z such that $numeracy(i) = numeracy(z)$. γ_i^{Hypo} determines changes in the internality utility and the probability of selection of bulb j by highly numerate individual i. For those who are not highly numerate, we assume $P_{ij}^{Hypo} = P_{ij}^{NES}$ and that the internality and experienced utilities are equal whether or not the hypothetical instrument is deployed.

5.2.2 A linear tax on expected energy consumption

In a first-best policy environment, a tax would align private decisions with the decision-maker's true preferences and exactly close the consumer's internality. The optimal policy instrument would include a set of heterogeneous taxes just equal to the dollar value of the internality; an optimal private tax, $t_i^* = \frac{(\theta_i^R - \theta)}{\eta_i}$, would deliver the additional (dis)utility equal to the utility gap between the rational benchmark and observed levels of sensitivity to consumption. In addition, it would address the marginal external cost of consumption. If the external costs were the only source of non-optimality, the tax would be a constant Pigouvian tax. A first-best world would include a set of heterogeneous taxes that addresses both the internality and externality.

We examine a second-best setting in which the policymaker cannot set individual-level taxes. The policymaker chooses one rate that optimizes a value function trading off distortions in consumer choice, reduced internalities, and reduced external costs of energy consumption:

$$\begin{aligned} t^* &= argmax_t \mathbb{E}\left[Value_{Tax}(t)\right] \\ &= argmax_t \mathbb{E}\left[(CS^{exp}_{Tax}(t) - CS^{exp}_{NES}) - (CS^{int}_{Tax}(t) - CS^{int}_{NES}) - (ECE_{Tax}(t) - ECE_{NES})\right] \end{aligned} \tag{23}$$

Equation 23 references NES values since the no-tax and NES choice probabilities, internality utility, experienced utility, and external costs are the same. Analogous to the hypothetical alternative label case, we introduce a term, γ_i^{Tax}, that captures the degree to which the tax affects the individual's marginal utility from energy consumption. In particular, $\gamma_i^{Tax} = \eta_i \cdot tax - rate$. γ_i^{Tax} substitutes for γ_i in Equation 17 and allows us to calculate I_{ij}^{Tax} and P_{ij}^{Tax}.

We assume that tax revenues are returned to the population such that the expected value of the tax return across the population equals the expected value of the tax paid.[24] Thus, while the tax changes both P_{ij} through its impact on purchase prices and the magnitude of the internality, we assume it has no consequence for the individual's expected experienced utility.

Since damages are linear in energy consumption, we examine a linear tax program in which the tax on product j, τ_j, $=$ *tax rate* $\cdot W_j$. We examine rates smaller than \$1.59/W, which is the undiscounted sum of external and private costs of electricity consumption over the lifetime of the bulb. The optimal rate applies only to a market in which all alternatives are CFL bulbs. The tax rate should otherwise be adjusted to account for the lifetimes of the bulbs.

5.3 Comparing the Instruments

Table 5 summarizes the value of the three instruments. The increase in experienced utility is counter-intuitive: if individuals were optimizing across all attributes except consumption, we would expect experienced utility to decrease, as the instruments distort choice relative to the pre-instrument setting. However, price is positively correlated ($\rho = 0.47$) with the level of consumption; instruments that increase the sensitivity to energy consumption reduce disutility not only from consumption but also from higher prices. Since the bulbs in the choice set used

[24] If the marginal utility of wealth decreases in wealth, there is an additional gain if returns are preferentially directed to lower income individuals.

to simulate the effects of the instruments have a narrow band of power ratings (13 – 16W), a larger portion of the improvement in experienced utility stems from a lower expected price than from a lower expected consumption level. Specifically, 73% of the improvement associated with the Energy Star label is attributable to the lower expected price; for the hypothetical and tax instruments, the share is 58% and 55%, respectively.

	Energy Star	Hypothetical Label	Tax (t = $0.24/W)
Reduction in Internality Utility			
Group A	$11	-$62	-$191
Group B	-$698	$135	$363
Group C	$856	$856	$2,093
Group D	-$2,710	-$459	-$1,615
All groups	-$2,540 -$1.64	$470 $1.21	$650 $0.42
Increase in Experienced Utility			
Group A	$27	$1	$2
Group B	$50	$2	$5
Group C	$39	$5	$15
Group D	$84	$4	$13
All groups	$200 $0.13	$11 $0.03	$35 $0.02
Reduction in External Cost			
Group A	$3	$0	$1
Group B	$6	$1	$2
Group C	$6	$1	$6
Group D	$10	$1	$3
All groups	$25 $0.02	$4 $0.01	$11 $0.01
Total Increase in Value	-$2,314 -$1.49	$485 $1.25	$696 $0.45
Scaled to all U.S. Households	-$112M	$6M	$34M

Table 5: In the presence of heterogeneity, a linear tax outperforms both the Energy Star program and a hypothetical label specifically targeting high numeracy individuals. In the "Total" rows, the top number quantifies the impact across the entire population and the bottom number, the per-capita impact. The final row scales the impact across the 1,550 households in the study to the population of U.S. owner-occupied households. The scaling of the hypothetical label's value adjusts for the proportion of our sample that were highly numerate.

The main implication of Table 5 is that both the hypothetical linear tax and targeted instrument outperform the Energy Star label. Our simulation suggests that the use of the Energy Star label instead of a per-power rating tax implies a loss in value of $3,000 within our participant set. If owner-occupied households in the U.S. responded similarly and were to purchase a bulb each in a given year, this loss would scale to $146M per year.[25]

[25] We scale the value of each instrument by the product of (1) the ratio of the total number of U.S households

The relative performance of the three instruments is driven in large part by their impacts on internalities and not on externalities. On the one hand, this reflects our decision to restrict the simulation bulb choice set to bulbs of 800 – 1000 lumens. On the other hand, this restriction may reflect how consumers make their bulb purchase decisions: bulbs are installed in a variety of locations throughout the house, and the search for bulbs may be limited to those within a particular lumen range and therefore a specific range of brightness. Since the variation in power requirements for a given range is relatively small, the reductions in external cost are unlikely to be large. Nonetheless, the Energy Star label delivers a reduction in external costs that is more than double that offered by the optimal tax. If the goal of policymakers is solely to maximize the reduction in externalities, the Energy Star label is the natural choice.

The larger reduction from the Energy Star label stems from its ability to not only change participants' sensitivity to consumption information but also generate a decision utility from the label itself. Thus, the Energy Star label affects the probability of choice through both γ_i, the coefficient on the interaction between the Energy Star and consumption, and λ_i, the coefficient on the Energy Star label. Since λ_i is negative for only 60 participants, the latter almost always increases the probability that goods with lower consumption levels are selected.

While the Energy Star yields the greatest externality reduction, it increases the internality utility, while the alternatives reduce it. Each instrument exerts heterogeneous impacts on the internalities, as documented by the positive and negative reductions in internality utility observed for the four different groups. However, since it is a blunt instrument, the Energy Star strikes the worst balance between the value of correct and incorrect changes in internalities. Figure 6 highlights the better balance achieved by the continuous tax rate. The optimal tax rate of \$0.24/W is almost exactly equal to the tax rate at which the marginal value of internality corrections is zero. The tax program allows the policymaker to trade-off the values of correct and incorrect changes in internalities. Finding 4 summarizes our comparison.

Finding 4: *Though the Energy Star yields a greater reduction in external costs than hypothetical tax and label alternatives, the latter are more valuable overall because they strike a better balance between the benefits and costs of internality mitigation and exacerbation.*

(approximately 115M) to the 1550 households in our sample and (2) the share of households that are owner-occupied. We use 65.2% for the latter, per data from the U.S. Census Bereau (2014).

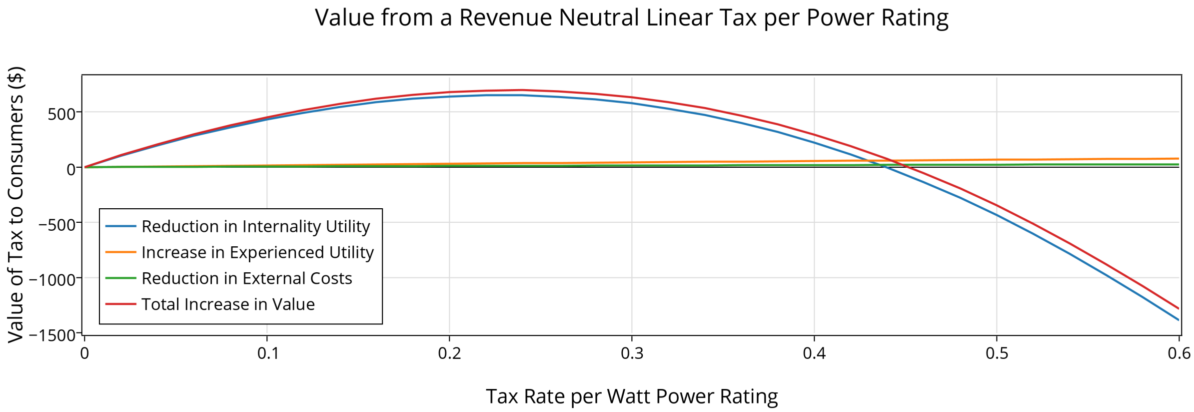


Figure 6: Assuming a revenue neutral tax program, the expected value of the tax is maximized at $\approx \$0.24/\text{W}$. The close match between the total value and internality reduction curves reflects the fact that internality reductions underpin the value in the instruments considered.

In Section 4, we observed that the effects of the Energy Star on internalities were associated with high numeracy and NEP. Finding 4 holds even upon including only these individuals. Among highly numerate individuals, the Energy Star, hypothetical label, and tax yielded values of -\$0.85, \$1.25, and \$1.09 per capita, respectively. Similarly, among those with high NEP, the corresponding values are -\$1.62, \$0.80, and \$0.30 per capita.[26] The lower value of the Energy Star for high-NEP individuals follows from our observation in Section 4.3 that highly numerate individuals were more likely to be binned in Group C and high-NEP in Group D.

5.4 Robustness Checks

We conduct three robustness checks on Finding 4. Check one uses three subsamples. The first includes only those for whom prediction accuracy improves upon using individual-level coefficients. The second includes only the 654 participants for whom γ_i is significantly different from 0 at the 0.05 level. Our third uses only the 367 individuals for whom we can reject the joint hypothesis that $\gamma_i = 0$ and $\theta_i = \theta_i^R$ at the 0.05 level.[27] In all cases, Finding 4 holds.

The second check asks whether Finding 4 holds across all experimental conditions. If responses differed by condition, our valuation may be biased by its use of the same coefficient

[26] These values reflect tax rates optimized and hypothetical label impacts defined on the full sample.

[27] We perform this test by simulating draws from the correlated distributions, assuming first that γ and θ are centered at the estimated values of γ_i and θ_i and next that they are centered at the null values of and θ_i^R. We use a chi-squared goodness of fit test with degrees of freedom equal to one fewer than the number of draws.

distributions across conditions. We value the Energy Star and the hypothetical programs by fitting mixed logit models and deriving individual-level coeffcients specific to each experimental condition. We re-derive an optimal tax for each condition and re-define the hypothetical targeted label such that it addresses the median internality observed for each high numeracy level within the specific condition. The directional results remain the same in all conditions, with the hypothetical tax and targeted instrument yielding higher value than the Energy Star.

However, Finding 4 is sensitive to the assumed mixing distribution. Coefficients from an ML model that constrains the Energy Star coefficient to be positive imply that the program is more valuable than the hypothetical instruments. This alternative mixing assumption implies greater reductions in internalities; while our baseline assumption groups 889 participants in Groups A and C, the model with a log-normal Energy Star coefficient bins 1239 subjects in these groups. Since the directional effect of the Energy Star is theoretically ambiguous, it is difficult to justify the lognormal distribution.[28] Nonetheless, the reversal in valuation illustrates the benefit of determining the mechanisms by which the Energy Star operates.

6 Conclusion

Consumers of energy-consuming goods are often insufficiently attentive to the energy consumption attribute of alternatives. The Energy Star label attempts to increase its salience. However, the label may do so only for some consumers while providing a license to ignore the attribute for others. This possibility implies two questions. First, do individuals with particular characteristics respond to Energy Star certification in systematically different ways? Second, what do these differences imply about the value of the Energy Star for consumers?

We used a mixed logit model of stated choice data to answer these questions. The Energy Star program appears to be of lower value to consumers than the hypothetical alternatives we evaluate. We separately quantified the impact of the program on internality consumer surplus, experienced consumer surplus, and the external costs of electricity generation. If we consider only the latter, the value generated by the Energy Star program exceeds that by its hypothetical competitors by a factor of at least two. For the policymaker primarily interested in reducing

[28] Moreover, the prediction accuracy of 56.6% is lower than that with our base assumption (60.2%).

externalities associated with energy consumption, the Energy Star thus remains a viable option.

The greater reduction in externalities is offset by a greater increase in internalities among consumers. When scaled across all owner-occupied households in the U.S., the Energy Star label would deliver a \$0.7M greater reduction in external cost relative to the hypothetical tax but an impact on internalities that is \$154M worse than that from the tax. While taxes aimed at the reduction of externalities may yield a "double dividend" by also addressing internalities (Allcott, Mullainathan, and Taubinsky, 2014), our results suggest that non-pecuniary measures such as the Energy Star label could yield "negative dividends."

The poor relative performance of the Energy Star stems from the situations in which it increases and decreases consumers' valuation of savings in energy consumption among those who, in its absence, already overvalue or undervalue them, respectively. In these cases, the Energy Star increases internalities. While these effects exist in the hypothetical programs, they are not as severe. The assumed targeting of the hypothetical label allows it to better match the change in utility coefficients to that required to close internalities across the target population. The tax rate balances the reductions and increases in internality levels that obtain across the heterogeneous population. Since internality effects drive the majority of value delivered by these instruments, we observe that the optimal tax rate is almost exactly equal to the level at which the marginal value of internality corrections is zero.

There are several fruitful avenues for further study. A first extension would include strategic responses by firms. A second is the design of eco-labels that are optimized for the heterogeneous impacts they will have on the target population. The third avenue seeks to reduce the empirical burden of label design. This reduction will require a better understanding of the decision mechanisms by which eco-labels affect consumers and the development of theory that can offer normative guidance as to whether a particular label will deliver greater value than, e.g., a tax program. It would be particularly useful to understand whether the Energy Star and other eco-labels indeed focus individuals' attention on consumption information, permit the consumer to ignore this information, or both. Absent such theory, our current recommendation to policymakers is to deploy either pecuniary or non-pecuniary measures intended to draw attention to a particular attribute of alternative goods only after characterizing their potentially heterogeneous effects in the target population.

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