CESifo WORKING PAPERS

10335
2023

March 2023

Do Consumers Acquire Information Optimally? Experimental Evidence from Energy Efficiency

Andrea La Nauze, Erica Myers

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 10335*

Do Consumers Acquire Information Optimally? Experimental Evidence from Energy Efficiency

Abstract

We use an experiment to test whether consumers optimally acquire information on energy costs in appliance markets where, like many contexts, consumers are poorly informed and make mistakes despite freely available information. To test for optimal information acquisition we compare the average utility gain from improved decision making due to information with willingness to pay for information. We find that consumers acquire information suboptimally. We then compare two behavioral policies: a conventional subsidy for energy-efficient products and a non-traditional subsidy paying consumers to acquire information on energy costs. The welfare effects of each policy depend on the benefits of improved decisions versus the losses of mental effort (from the information subsidy) or distorted choices (from the product subsidy). In our context, information subsidies dominate product subsidies. In a variety of settings where decisions are made and information is delivered online, paying for attention could more effectively target welfare improvements.

JEL-Codes: D910, D120, D830, Q410.

Keywords: endogenous information acquisition, behavioural bias, information interventions, energy efficiency.

Andrea La Nauze
University of Queensland / Australia
a.lanauze@uq.edu.au

Erica Myers
University of Calgary / Canada
erica.myers@ucalgary.ca

March 16, 2023
We acknowledge funding from the University of Pittsburgh Social Science Research Initiative. We thank Acadia Hall and Na Zhang for outstanding research assistance and Fiona Burlig, Tatyana Deryugina, Iza Ding, Gordon Leslie, Leslie Martin, Rob Oxoby, Mar Reguant, Marta Serra-Garcia, participants at MidWest Energy Fest, Monash Environmental Economics Workshop, CESifo Area Conference on Energy and Climate Economics, the University of Melbourne, the University of Queensland, and the Florida Applied Micro Seminar for helpful comments. This research has been pre-registered at the American Economic Association's registry for randomized controlled trials, with ID number AEARCTR-0006656. The authors have no material financial interests related to this research.

1 Introduction

Despite readily available information, consumers are often poorly informed and as a result, make mistakes in a variety of decision-making settings including health care, financial investments, and energy efficiency (e.g., Hortaçsu and Syverson, 2004; Choi, Laibson and Madrian, 2010; Handel, 2013; Bronnenberg et al., 2015; Handel and Kolstad, 2015; Bhargava, Loewenstein and Sydnor, 2017; Choi, Laibson and Madrian, 2010; Houde and Myers, 2019). The failure of consumers to acquire valuable information could be a rational response to "frictions", in the form of costly time and attention required to acquire information. Or, it could result from "mental gaps", psychological distortions in how consumers gather, process, and attend to information (Handel and Schwartzstein, 2018).

In this paper, we go beyond identifying the consequences of imperfectly informed consumers to distinguish between these two possible causes. This endeavor is important for two main reasons. First, empirical evidence on whether frictions or mental gaps drive consumer information acquisition determines the suitability of different modeling approaches. Rational inattention models, for example, assume that individuals optimally trade off the costs and benefits of acquiring information (Sims, 2003; Woodford, 2012; Caplin and Dean, 2015; Gabaix, 2014; Maćkowiak, Matějka and Wiederholt, 2021). Alternative models incorporate mental gaps, for example by allowing consumers to have the wrong decision model or suffer from biased beliefs and overconfidence (Schwartzstein, 2014; Bénabou and Tirole, 2002). Second, whether frictions or mental gaps explain information acquisition matters for welfare and policy across innumerable settings where information is readily available. If consumers acquire information optimally in response to frictions low-cost policies that reduce those frictions will improve welfare. However, in the presence of mental gaps, consumers will make mistakes even in the absence of frictions, and more heavy-handed policy, such as subsidizing information acquisition could better target welfare improvements (Sallee, 2014).

Our first contribution is to design and implement a sufficient-statistic test for whether consumers optimally acquire information. Our test builds on the existing literature studying whether decision makers acquire more information when the stakes are higher (e.g., Bartoš et al., 2016; Hoopes, Reck and Slemrod, 2015; Fuster et al., 2018; Gabaix et al., 2006). Testing for *optimal* information acquisition is challenging because it requires variables that are typically unobserved: individual measures of willingness to pay for information, the utility value of information, and cognitive effort costs associated with processing information. We design a multi-stage experiment using incentive-compatible mechanisms to elicit these parameters. In our experiment, consumers choose between competing products and have the option to acquire information on a potentially non-salient product characteristic. The product-characteristic information is valuable if it causes the consumer to make a better product choice that leads to higher utility. We quantify the utility gain due to improved choices from information using within-subject changes in product willingness to pay. Conditional on effort costs and under risk neutrality, if consumers optimally acquire information, the average realized value of information across consumers should increase one-for-one with willingness to pay for that information.

We focus on appliance markets, where it has been established that lack of information leads to imperfect decision making (e.g., Allcott and Taubinsky, 2015; Davis and Metcalf, 2015; Beattie, Ding and La Nauze, 2022). Like many consumer durables, operating costs and the expected lifespan of appliances are important determinants of overall costs. Thus, if consumers are imperfectly informed about or inattentive to these characteristics, they may make errors in their product purchase decisions.

We strongly reject that consumers optimally acquire information, indicating that errors in decision making are the result of mental gaps and not purely the result of frictions. On average, the value of information revealed through changes in informed consumers' product choices does not move one-for-one with willingness to pay for information. In fact, the correlation is 0.04, the result of consumers both over- and under- valuing information.

Our next contribution is to understand whether competing decision models are consistent with observed behavior, and in particular to understand how biased beliefs affect information acquisition. To begin with, we reject that consumers' willingness to pay for information is correlated with factors that indicate their product choices might be marginal to information (the uncertainty in their own prior beliefs or the strength of their initial preference for one product over the other) as the rational model predicts. Using an individual-level measure of bias, we also reject that otherwise rational consumers acquire information suboptimally due to biased beliefs. Instead, the probability of undervaluing information is correlated with initial preferences for energy efficiency, and proxies for consumers' political leaning, factors that are consistent with models of confirmation bias and motivated reasoning where individuals seek out information to confirm beliefs or a preferred state of the world (Kunda, 1990; Epley and Gilovich, 2016; Charness and Dave, 2017).

Our final key contribution is to propose and analyze a non-traditional subsidy to address mental gaps in information acquisition that pays people to acquire and process information. We show that this subsidy is a function of reduced form sufficient statistics from our experiment (e.g. Mullainathan, Schwartzstein and Congdon, 2012; Allcott and Taubinsky, 2015; Farhi and Gabaix, 2020) and compute the optimal subsidy in our setting. A single public entity that can gather, organize and disseminate information at low marginal cost may improve efficiency by reducing information frictions. However, if consumers irrationally ignore freely-available information, public provision of information may be less effective than anticipated. In this case, incentivizing consumers to view and attend to information could improve welfare. This type of intervention is increasingly relevant given the prevalence of online shopping and has been implemented in practice. For example, the Victorian Government in Australia offers a $250 incentive for consumers to compare the costs of rival electricity plans on their price comparison website.[1]

We compare the properties of this non-traditional information subsidy to a more conventional product subsidy (Allcott and Taubinsky, 2015). The optimal information

[1] See https://compare.energy.vic.gov.au/, accessed March 16, 2023.

subsidy is equal to the average undervaluation of information by consumers whose information choice is marginal to the subsidy. The subsidy improves welfare because the value of improved product choice from information outweighs the effort cost of attending to information. The optimal product subsidy is equal to the average bias in product choice of consumers whose product choice is marginal to the subsidy. The product subsidy improves welfare because the gains from improved product choices outweigh the losses from any distortions in product choices the subsidy introduces.[2] Whether a product or information subsidy is preferred depends on the magnitude of the gains from improved decisions from each instrument versus the losses of mental effort (from the information subsidy) or distorted choices (from the product subsidy). Our results indicate that the optimal information subsidy is approximately $9 on a $20 package of LED bulbs while the optimal product subsidy is approximately $12. In our setting, the information subsidy dominates, increasing welfare by 10 percent more than the product subsidy.

Our experiment is designed to recover sufficient statistics enabling us to test for optimal information acquisition and compute optimal policy responses. We implemented the experiment online using a representative sample of 1902 adults in the United States. The key parameters we require to implement the test are consumers' willingness to pay for information, their revealed value of information, and their cognitive or mental effort costs. In the experiment, consumers are allocated a budget to purchase one of two packages of light bulbs. One package consists of 24 halogen bulbs and the other of 12 more efficient light-emitting diode (LED) bulbs. Compared to other appliances, light bulbs are a relatively low-cost, common household purchase, making them particularly attractive for experimentation.

To measure the revealed value of information, we elicit consumers' relative willingness to pay for the light bulb packages before and after receiving information on the lifetime operating costs and durability of the bulbs. To do this, we use an incentive-compatible

[2] There will be some consumers who are induced to buy the more efficient product because of the subsidy but whose undistorted willingness to pay for the product is less than its marginal cost, generating a welfare loss.

multiple-price list, where consumers choose which package they prefer at a series of relative prices knowing that each choice has an equal probability of becoming their actual purchase. To elicit consumers' willingness to pay for information on lifetime costs, in between the two sets of light bulb choices consumers select whether to view the information at a series of positive and negative price points (i.e. reductions or increases in their budget). To make the choice incentive compatible, one of the price points is chosen at random, and the consumer's implied choice of whether to view the information at that price is implemented.

To elicit effort costs we mimic the task used to elicit willingness to pay for information, with one key difference. Instead of offering information that can improve product choices, we offer consumers similar information for obsolete light bulbs and elicit their willingness to accept to review this information and answer an additional question. As the information has no impact on product choices, it has a utility value of zero, and the elicited willingness to accept to undertake this task can be used to measure individual effort costs. During the experiment, we also measure each consumer's distribution of baseline and endline beliefs about the relative lifetime costs of each light bulb technology, elicit risk and time preferences, and collect demographic characteristics.

Our results contribute to several strands of literature. First, our study speaks to a growing body of work on inattention (see Gabaix (2019) for a recent review). We contribute to this literature by testing for optimality of information acquisition, which is important for welfare and policy in a wide variety of contexts where information is easily accessible, though potentially underutilized. Our work is related to studies that test for optimality of other aspects of attention. For example, Howard (2022) finds that experts produce attention more efficiently than novices in online chess games. Bronchetti et al. (2022) find that people do not optimally acquire so-called "bandwidth enhancements" to manage future attention.[3] Our findings also add to the literature in economics and psychology on confirmation bias and motivated reasoning. Recent evidence suggests

[3]Recent work also tested various predictions of rational inattention models in the laboratory (e.g., Caplin, Dean and Martin, 2011; Khaw, Stevens and Woodford, 2017; Dean and Neligh, 2018).

incentives are a powerful solution to overcome avoidance of moral information and belief in misinformation (Zimmermann, 2020; Serra-Garcia and Szech, 2022). The findings of our experiment speak directly to how incentives to acquire information overcome biased acquisition of information by consumers. The fact that consumers are not optimally acquiring information on light bulbs, a relatively common consumer purchase, suggests that there are likely other purchase and choice decisions where people are irrationally underinformed and incentives may be an effective intervention.

Our results also build on the nascent behavioral public economics literature describing optimal policy with behavioral agents (e.g., Bernheim and Rangel, 2009; Mullainathan, Schwartzstein and Congdon, 2012; Taubinsky and Rees-Jones, 2018; Farhi and Gabaix, 2020; List et al., 2022). Much of the previous work focuses on optimal allocation policies, such as quantity standards or taxes, to correct distorted product choice (e.g., Allcott, Mullainathan and Taubinsky, 2014; Allcott, Lockwood and Taubinsky, 2019; Houde and Myers, 2019), or, in some cases, on policies that reduce information frictions (e.g., Handel, Kolstad and Spinnewijn, 2019). We add to this literature by considering a non-traditional policy designed specifically to address mental gaps in information acquisition. We provide direct empirical evidence on the magnitude of distortions in consumer information acquisition. We then derive and show how the welfare impacts of optimal information subsidies and optimal product subsidies can be compared.

Finally, our results speak to our understanding of the impact of information provision and labeling interventions. There is minimal evidence supporting the efficacy of government-mandated information disclosure programs across a wide range of contexts (see reviews in Winston, 2008; Loewenstein, Sunstein and Golman, 2014; Ho, Ashwood and Handan-Nader, 2019). Our results suggest consumers misperceive the value of attending to and incorporating information, so labeling and disclosure policies may have limited effects. This is of particular importance in the context we study. Appliances and building-related equipment account for almost all the energy used in buildings, which as a sector accounts for around 40% of U.S. energy consumption and associated greenhouse gas (GHG) emissions (Baldwin et al., 2015). Despite the fact that energy labeling policies for energy-using durables have been in place in the U.S. since the 1980s, a large share of consumers misperceive the associated costs (Houde and Myers, 2019). When people lack information or are inattentive to the operating costs of energy-using durables, they will sub-optimally invest in efficiency even under carbon pricing policies. We demonstrate that mental gaps in information acquisition about operating costs may be an important driver of investment inefficiencies and show that a non-traditional policy instrument, information subsidies, can target welfare improvements more effectively than conventional product subsidies.

2 Sufficient Statistic Test of Optimal Information Acquisition

We develop a straightforward test of optimal information acquisition comparing, for a group of consumers, ex-ante willingness to pay (WTP) for information with the ex-post value of that information in terms of improved decision making.

Suppose a consumer is purchasing an appliance and can choose to purchase information about the operating costs of different models (e.g. differences driven by the energy consumption and the appliance lifetime). We begin by assuming consumers only gain value from information through improving this product choice, for example, there is no external value of information outside the choice of which light bulb to buy. Let the utility of an informed, risk-neutral individual i for appliance j be:

$$U_{ij} = \nu_{ij} - p_j - \kappa_{ij} \tag{1}$$

where ν_{ij} includes the consumer's valuation of the appliance's characteristics that do not affect its operating costs (e.g. color), p_j is the price of appliance j and κ_{ij} is the consumer's lifetime operating cost of appliance j. When individuals are not perfectly informed about κ_{ij} they have an estimate k_{ij} where $\kappa_{ij} = k_{ij} + \epsilon_{ij}$ and ϵ_{ij} is an error term that is mean zero if consumers have unbiased beliefs. Therefore, an uninformed individual's experienced utility, which they actually receive from their choice, may differ from their choice utility, which they anticipate when they are uninformed about product costs. For an informed individual, the choice utility and the experienced utility are the same.

Ex post, the realized value of information is the gain in experienced utility from becoming informed. Information only changes experienced utility if it leads the consumer to choose a different appliance than they otherwise would have. Consider a consumer choosing between two appliance models: an efficient model 1, and an inefficient model 0. Let $l \in \{0, 1\}$ denote the preferred product of the informed consumer and $m \in \{0, 1\}$ denote the preferred product of the uninformed consumer at prices p_l and p_m. If $l = m$ (i.e. the preferred products of the informed and uninformed consumer are the same) then the realized value of information is zero. In this case, the consumer's experienced utility from the preferred product may be higher than their choice utility, but they would have realized this higher utility regardless of whether they become informed. If $l \neq m$, then the realized value of information is the difference in experienced utility between products: $U_{il} - U_{im}$. Define the informed consumer's relative willingness to pay for product l: $W_{il} = (\nu_{il} - \kappa_{il}) - (\nu_{im} - \kappa_{im})$ (the utility derived from the non-price characteristics of purchasing product l versus product m) then the ex-post value of information can be written:

$$V_i = W_{il} - (p_l - p_m), l \neq m \tag{2}$$

Ex ante, to choose whether or not to acquire information, the consumer forms an expectation about the value of information $E_i[V_i]$ (where we use subscript i on the expectation operator E to denote this expectation is from the perspective of the consumer). This reflects the difference between the expected value of the good maximizing experienced utility minus the utility of the good maximizing choice utility:

$$E_i[V_i] = E\left[\max_j(\nu_{ij} - p_j - \kappa_{ij})\right] - \max_j E\left[\nu_{ij} - p_j - k_{ij}\right] \tag{3}$$

If consumers correctly assess the costs and benefits of acquiring information they will be willing to pay this expected value of information net of any idiosyncratic cognitive effort cost e_i. Then a risk-neutral consumer's willingness to pay for information W_i^I is:

$$W_i^I = E_i[V_i] - e_i \tag{4}$$

For any individual, the expected value of information may not equal the realized value of information given there is a random component to individuals' uninformed beliefs. However, across the population, if consumers are optimizing, the expectation of the revealed value of information should equal the mean of the consumers' ex ante expectations of its value:

$$E[V_i] = E[E_i[V_i]] \tag{5}$$

Solving for $E_i[V_i]$ in 4 and substituting the expression into 5 gives:

$$E[V_i] = E[W_i^I + e_i] \tag{6}$$

$$E[V_i|W_i^I, e_i] = W_i^I + e_i \tag{7}$$

Under risk neutrality, this equation suggests two possible avenues for a test of optimal information acquisition. First, if all the components of equation 6 are observable, then one can compare if, on average, the left-hand side is equal to the right-hand side. Second, from equation 7, if effort cost is not correlated with both W_i^I and V_i, the sufficient reduced form statistics necessary to implement the test are simply a measure of consumers' realized value of information and their willingness to pay for that information. In this case, a necessary condition for optimal information acquisition is that the population expectation of the realized value moves one-for-one with willingness to pay.

In the next section, we outline the experiment enabling us to recover revealed preference estimates of W_i^I and V_i as well as information that will allow us to test the assumptions of our model, including measures of risk-preference, effort costs and other potential drivers of the value of information.

3 Experimental Design and Implementation

We designed an online experiment in consumer choice that enables us to test for optimal information acquisition. In our experiment, consumers have the opportunity to purchase light bulbs and information on the full lifetime costs of the bulbs. Consumers are offered two types of bulbs that are similar along many product dimensions but differ substantially in their lifetime energy costs and durability: light emitting diode (LED) bulbs and halogen (incandescent). LED bulbs are superior in terms of energy use and durability, but consumers may have high willingness to pay for incandescents, for example, because of strong preferences for light quality. The experiment consists of the following modules:

1. Eliciting the distribution of consumer beliefs on the expected lifetime costs of bulbs
2. Eliciting relative willingness to pay for the energy-efficient light bulb package $\widehat{W_{i1}}$ using an incentive-compatible mechanism
3. Eliciting willingness to pay for information W_i^I using an incentive-compatible mechanism
4. Randomizing the realized cost of information p^I and observing random receipt of information $T_i = \{0, 1\}$ conditional on W_i^I
5. Re-eliciting relative willingness to pay for the energy-efficient light bulb package W_{i1} using an incentive-compatible mechanism
6. Re-eliciting the distribution of consumer beliefs on the expected lifetime costs of bulbs
7. Collecting consumer characteristics
8. Measuring willingness to accept W_{ie} for an effort task where $e_i = f(W_{ie})$ using an incentive-compatible mechanism

At the beginning of the experiment, participants were informed that one in ten people who complete the experiment would win a prize worth up to $100. The value of the prize was determined by their choices and random price draws, and consisted of any light bulbs that were purchased as part of the incentive-compatible WTP elicitations and any remaining budget on an Amazon gift card. Participants were also paid for completing the experiment.[4]

3.1 Belief Elicitation

To enable us to test alternative theories of behavior we measure the full distribution of consumer beliefs about the relative lifetime costs of the bulbs before and after making this information available (Modules 1 and 6). To do so we asked consumers to consider the total costs of lighting one lamp for 10 years for an average of 3 hours per day given a single bulb purchase price of $2. We then asked two follow-up questions. First, consumers were asked whether they thought the total cost would be higher using the LED or halogen bulbs. Then, consumers were asked to place 10 tokens in pre-determined ranges according to their expectations about the difference in total cost.[5] To assist consumers we asked them to suppose they were betting on the true costs using the 10 tokens and provided hints and examples. This latter task is a simplified version of the subjective elicitation task of Shrestha (2020). For each allocated token we compute the midpoint of the range and then for each consumer, we compute the mean and standard deviation of beliefs at baseline and at endline.

[4] The full experimental transcript can be accessed here. We sent light bulbs and gift cards to consumers, direct payments for survey completion were undertaken by panel providers contracted by Qualtrics.

[5] In their review, Delavande and Kohler (2009) provide evidence that probabilistic expectations elicited in surveys using similar tasks follow basic properties for probabilities, are correlated with qualitative measures of expectations, and are predictive of outcomes and behaviors.

3.2 Light Bulb Choices

In our experiment, consumers chose between two packages of light bulbs: a package of 12 light-emitting diode (LED) bulbs and a package of 24 halogen (incandescent) light bulbs. The packages were as similar as possible on the characteristics of color and lumens, were the same brand (GE) and the most common shape and fitting, but differed substantially in terms of energy consumption and durability. Basic information on the two packages, including wattage, which determines the electricity consumption of the bulbs, was provided to all consumers. To elicit WTP for the efficient bulb before and after information on lifetime costs (Modules 2 and 5), we used an incentive-compatible price list. Consumers selected their most preferred package at 17 price points for the LEDs relative to the halogens in the range -$60 to $60 where -$60 corresponds to the cost of the LED package being 0 and the cost of the halogen package being $60. The point at which consumers switch from one bulb type to another bounds their relative WTP for the package of LEDs. For example, if a consumer chose the package of halogens at a relative price of 0, and chose the package of LED bulbs at a relative price of -$3.75 then the consumer's WTP for LEDs is between 0 and -$3.75 (symmetrically, they have a WTP for the halogens of between 0 and $3.75). For our analysis, we take the midpoint of this range, so that this consumer would have a WTP of -$1.875 for the package of LEDs. If a consumer preferred one package at all prices between -$60 to $60, they were asked to provide the price at which they would switch to the alternative but were told this price would not impact their shopping budget, i.e. it was hypothetical.

Consumers were told that if they were a prize winner, one of the prices from the list would be picked by the computer (with each row having an equal chance of being picked) and they would be sent the package and any remaining shopping budget as an Amazon gift card. For those with WTP for the LED between -$60 to $60 this is an incentive-compatible elicitation, meaning it is in consumers' interests to reveal their true WTP. For those with WTP outside this range, it is in consumers' interests to reveal that their true value is outside the range and there is no strategic advantage to over- or under-stating WTP.

Prior to the baseline light bulb choice, the price list format was explained to consumers using the example of two cereal products. The example showed all possible monotonic answers to the prices given (referring to these answers as "logical"). To proceed through the experiment, participants had to correctly identify monotonic and non-monotonic answers. If consumers submitted non-monotonic responses in the remainder of the experiment they were prompted once to answer again. If they continued to answer non-monotonically they were not considered a quality response and were not eligible for the prize.[6]

We use the baseline and endline light bulb choices to calculate the value of information for all consumers receiving information in the experiment. From Equation 2, at a given relative price, the revealed value of information is the endline relative WTP for the preferred product minus its relative price if the endline preferred product differs from the baseline. As we observe the preferred product at 17 different relative prices, each with an equal chance of being realized, we take the average of the value of information across price points to calculate V_i for the experiment.

3.3 Information Choice and Information Treatment

After their first set of light bulb choices, in Module 3 we elicited participants' WTP for information on the total cost of using the light bulbs using a "staircase" procedure. This incentive-compatible procedure is a streamlined version of a price list requiring fewer choices and providing comparable responses (Falk et al., 2016, 2018).[7] We first explained to consumers that information would be available to them before they made a second set of light bulb choices. We then used a series of scenarios to elicit their WTP for the lifetime cost information. Appendix Figure A1 shows how the module started while Appendix Figure A2 outlines the full staircase. Depending on their response to

[6]Our contract with Qualtrics stipulated that we would not receive these low-quality responses.

[7]Unlike the price list there is no possibility for consumers to submit non-monotonic responses in the staircase.

the preceding questions, the consumer is offered an increase in their shopping budget for viewing/not viewing the information up to a value of $10. Each consumer is asked up to four questions and their responses to these questions allow us to bound their WTP in the same way as a price list. As with the price list, we take the midpoint of the WTP range revealed by the staircase.[8] If consumers always answered they wanted information or did not what information, consumers were asked to state their WTP/willingness to accept to receive the information.

Once the staircase was completed, in Module 4 each consumer's choices were summarized for and they were then told the computer would randomly draw a payment amount and if their WTP/willingness to accept was above that amount they would receive the information. Before the draw occurred, they were given the opportunity to revise their responses.

In the experiment, consumers were offered one of eleven payment amounts ranging from -$10 to $10 to view information. To ensure that our sample contained sufficient consumers with low WTP for information, we set the probability of the largest subsidy ($10) to 0.6. All other payment amounts were offered with probability 0.04. Depending on their WTP for information, and their random price draw, some consumers were then provided with the lifetime cost information. Appendix Figure A3 shows the information provided, which is based on the mandatory product energy label provided by manufacturers. Over 10 years, the costs of using LED light bulbs are expected to be $60 less than the costs of using halogen light bulbs. In order to proceed from the information screen to the rest of the experiment, consumers that were provided with the information had to correctly answer a multiple-choice question identifying the difference in operating costs of the bulbs over 10 years.

[8]For example, if a consumer first answered that they would like information when no change in their shopping budget was offered, they were then asked if they would prefer an increase in their shopping budget of $5 and not to view the information. If they would prefer this shopping budget increase, they were then offered a lower amount of $2.50 to not view the information. If at this point they chose information then their WTP for information would be the midpoint of $3.75.

3.4 Consumer Characteristics

In addition to age, gender, income, and education, in Module 7 we asked consumers whether they pay electricity bills, the number of light bulb sockets in their home, how many people live in their home, and we measured their risk and time preferences using the staircase procedures of Falk et al. (2016, 2018).

3.5 Effort Task

Finally, in Module 8, we designed an incentive-compatible task to measure variation in effort costs, the additional costs of acquiring information that are idiosyncratic and unobservable. To do so, we asked consumers whether they would be willing to review information on the lifetime cost of obsolete light bulbs and answer an additional question in return for a series of payments presented according to a staircase.[9] As this information has no impact on light bulb purchasing decisions it has an expected utility value of zero in the experiment. From Equation 4 if the expected utility value of information is zero, then willingness to accept to view the information is equal to the cost of effort required to process it. As the cognitive task of processing the information on obsolete bulbs is almost identical to the cognitive task of processing information on light bulbs in our experiment, we take this measure as a proxy of each individual's effort cost.

3.6 Data and Implementation

Our experiment was implemented online using the Qualtrics platform from October 2020 to February 2021.[10] The target sample were residents of the United States ages 18 and over, matched to census probabilities for age, gender, and education. Appendix Table

[9]As with the previous staircase, consumers are informed that one of the prices will be drawn at random and their choices will determine whether they undertake the task. Appendix Figure A4 outlines the full staircase.

[10]We ran an initial pilot in early October. In response to feedback from Qualtrics we redesigned some aspects of the experiment including simplifying the belief elicitation task. Details of the pilot are available on request.

B1 reports that the actual sample matches well on these target probabilities. The target sample size was 2000. Descriptive statistics of the sample are provided in Appendix Table B2. Our final sample consists of 1902 consumers. Of the 1902 complete responses, 1435 received the information treatment. Consumers took an average of 3 minutes 45 seconds to complete the baseline light bulb WTP elicitation and 1 minute 48 seconds to complete the endline light bulb elicitation. Those who viewed the information spent an average of 2 minutes on the information screen.

There are two well-known issues with price list elicitations. First, consumers may answer non-monotonically. In the implementation, Qualtrics removed any consumer who answered the bulb choice price lists non-monotonically after being prompted to re-answer the question, hence we do not observe non-monotonic responses to the price lists. Second, consumers with a WTP outside the price list report a stated WTP, which is unbounded and thus hypothetical. To remove the influence of outliers from responses to hypothetical questions, we winsorize the following variables at the 5 per cent level: standard deviation of beliefs, baseline and endline WTP for bulbs and information, and willingness to accept for the effort task.[11] In Section 4.1 we demonstrate that results are robust to alternative approaches to dealing with outliers.

Before we turn to this paper's primary hypothesis about optimal information acquisition, we first demonstrate that the impact of the information on consumers' decisions in our experiment closely aligns with previous literature. Notably, information increases consumers' WTP for the more efficient, LED light bulb and the mechanism appears to be that consumers are updating their beliefs in line with the information provided.

Figure 2 shows the difference in winsorized WTP for the LED between endline and baseline elicitations for the group receiving information and not receiving information. For those receiving information, there is a clear shift to the right in their WTP for the LED package after receiving information. Using the random cost draw as an instrument

[11] Appendix Figure B1 shows the distribution of each variable winsorized at the 1st and 5th percentiles. In our sample, 3.7% and 17.5% were censored towards the halogen and LED at baseline. At endline, 3.1% and 31.2% were censored towards the halogen and the LED respectively. This is in line with previous literature (e.g., Allcott and Taubinsky, 2015; Beattie, Ding and La Nauze, 2022).

for whether consumers view information, we find that the causal effect of information on WTP for the LED package is approximately \$17. The magnitude of the treatment effect is comparable to Allcott and Taubinsky (2015), who estimate the impact of light bulb energy cost information on WTP for bulb efficiency in a similar fashion (see Appendix B.2 for more detail).

Further, consumers in the informed group appear to update beliefs towards the information provided in the treatment. Using a simple Bayesian learning model, we find that the average treated consumer puts substantial weight (25%) on the information signal provided in the experiment relative to their priors (75%) in formulating their endline beliefs (See Appendix Table B11).[12] Among those receiving information, we also find that consumers who spend more time on the information screen or in reporting their beliefs appear to learn more from (i.e. put more weight on) the information provided (See Appendix Table B11).

4 Results

4.1 Testing Optimal Information Acquisition

We now turn to our test of optimal information acquisition, which compares the value of information with consumers' WTP for information. Figure 1 shows the distributions of the value of information and WTP for information in our sample. Panel (a) of Figure 1 shows the distribution of the winsorized value of information for the informed group. For around a third of consumers, the information has no value, meaning that it did not change their preferred bulb at any point in the price list. However, the mean value of information across all consumers was positive at \$8.36.

Panel (b) of Figure 1 shows the distribution of winsorized WTP for information for the

[12] We estimate the following model:

$$\Delta MeanBeliefs_i = \alpha(Signal - Prior_i) \times ReceivedInformation_i + \beta(Signal - Prior_i) + \delta W_i^I + \epsilon_i$$

, where α measures the "true" learning rate while β reflects spurious mean reversion. Whether consumers "Received Information" is random conditional on WTP for information W_i^I in the experiment.

group receiving information, which we use for our test of optimal information acquisition, and those not receiving information, which we do not include. Mean WTP for information among those receiving it was substantial, \$23.92. Of the 467 not receiving information, 68% had a WTP below the lowest price in the information price list (i.e. they were not marginal to the maximum subsidy we offered).

Recall from Equation 5, if consumers are risk neutral and their effort cost is not correlated with both W_i^I and V_i, then a test of optimal information acquisition is whether the revealed value of information increases 1 for 1 with WTP for it. Figure 3 plots this relationship for the subset of consumers that viewed information. From this figure it is clear that the line of best fit has a slope that is substantially lower than one. Individuals with low WTP for information appear to be undervaluing the impact of information on their product choice while individuals with high WTP for information appear to overvalue it.

Column (1) of Table 1 reports estimates from a more formal test of the hypothesis. We regress the realized value of information on WTP for information.[13] Standard errors are robust and observations are weighted by the inverse probability of selection into treatment to account for the uneven probability of treatment conditional on WTP for information.[14] With this initial approach, we strongly reject that consumers are obtaining information optimally, i.e. a slope coefficient of one. The value of information for consumers with zero WTP for it is on average \$7.50 while an increase in WTP for information of \$1 leads to an increase in the revealed value of information of \$0.04.

As mentioned above, a condition for this to be a valid test of optimal information acquisition is that effort costs are not correlated with both the value of information and WTP for it. If so, it would create an omitted variables bias on the slope coefficient. To address this concern, we use consumers' revealed willingness to accept to complete the

[13]We also consider a Poisson model specification. The results are consistent with the OLS presented here. See Appendix Table B12.

[14]For these regressions our sample is also truncated at a WTP for information of -\$8.75. Those with WTP less than -\$8.75 have a zero probability of receiving information. As this selection is a deterministic function of our independent variable our coefficients are not biased by this selection (Wooldridge, 2010).

effort task in the experiment as a proxy for effort costs in the information task. Recall the task was designed to mimic the effort required to process light bulb cost information for another type of information with no value in the experiment. Therefore, the proxy should be highly correlated with individuals' effort costs in the information task. In Appendix Table B3 we show support that our measure does indeed appear to be a good proxy for effort cost. In particular, we find those with higher willingness to accept in the effort task have lower WTP for information, are less patient and spend less time on the information screen if they view it in the experiment, relationships that we would expect to find if our measure captures variation in effort costs. Further, we find there is no correlation between willingness to accept for the effort task and the revealed value of information, which suggests that effort costs are unlikely to be driving omitted variables bias in our context. Indeed, when we include the effort cost proxy as a control in our regression of value of information on WTP for it (Column (2) of Table 1), we find no significant or economically meaningful difference in the coefficient of interest.

The test of optimality also requires an accurate representation of WTP, which can theoretically be influenced by choices in how we code responses to the price list. In columns (3) and (4) of Table 1 we consider whether WTP/accept answers outside of the bounds of our price list (thus revealed in an open-ended, not-incentive-compatible way) could be driving the results. In column (3), we restrict the sample to consumers with an incentive-compatible WTP for information within the bounds of the information price list. Then, in column (4) we further restrict the sample to consumers with an incentive-compatible willingness to accept within the bounds of the effort task price list. Neither of these restrictions significantly changes the coefficients, suggesting that responses outside the bounds of our experimentally defined price lists are not driving our findings. Further, our conclusions are not sensitive to other choices in how we: (1) winsorize values outside of the price lists (Appendix Figure B3), (2) impose sample restrictions to account for the quality of responses (Appendix Table B9), or (3) assign levels of WTP for information within each range of values isolated by the price list–e.g. median, lower bound, upper bound of the price ranges (Appendix Table B10).

We also consider the role of risk tolerance. If consumers are risk-loving and optimally acquiring information the expected value of information would increase by less than one with increases in WTP for information. However, for risk tolerance to drive the weak relationship between WTP for information and its revealed value that we find, consumers would have to be extremely risk-loving. In contrast (consistent with the literature (e.g., Falk et al., 2016)), we find the vast majority of consumers in our experiment are somewhat risk averse (see Appendix Figure B2 for the distribution).

Finally, we consider the possibility that consumers may value the information for future light bulb purchases outside of the experiment, which could lead to the value of information increasing by less than one for a one-unit increase in WTP for it. If this were the case, with optimally-behaving consumers, we would expect to find heterogeneity in the relationship between the value of information and WTP for it by a household's future demand for light bulbs. The difference in the expected annual lighting costs for LED versus halogen bulbs is primarily driven by the number of sockets in the home. For example, the expected annual savings of LED over halogen bulbs is approximately $600 for a home with 10 sockets and $1500 for a home with 25 sockets. However, we do not find any evidence consistent with homes with more sockets, and thus higher demand for lighting, having a weaker relationship between the value of information and WTP for it. Appendix Figure B4 displays this relationship for consumers with above and below the median number of sockets and there is no differential slope between the two groups. This suggests future demand for lighting is not a driving factor in the relationship between consumers' WTP for information and its value. Therefore, the relationship we see is not caused by consumers making optimal decisions about information that consider their future demand for light bulbs outside of the experiment.

4.2 Models of Information Acquisition

We have strong evidence that consumers are not acquiring information optimally. This suggests that consumers' lack of information about energy costs observed in other contexts is unlikely a rational response to the presence of "frictions", in the form of the time and attention required to acquire information (e.g., Maćkowiak, Matějka and Wiederholt, 2021). Rather, errors appear to be the result of "mental gaps", psychological distortions in how consumers make decisions including gathering, processing, and attending to information. In what follows we assess whether competing decision models are consistent with observed behavior.

4.2.1 Rational Information Acquisition

We begin by assessing whether consumers' WTP for information is correlated–even if suboptimally –with the potential gains from better decision-making as a rational information acquisition model would predict. Consider the utility function for uninformed individuals as presented in Section 2, where k_{ij} represents an estimate of the true lifetime operating costs $\kappa_{ij} = k_{ij} + \epsilon ij$. To derive testable predictions of this model, we provide structure on the error in beliefs ϵ_{ij}. To begin, we assume that ϵ_{ij} is a type 1 extreme value random variable with mean zero (beliefs are unbiased) and scale parameter ϕ_i (representing the consumer's ex ante uncertainty). If m is the appliance with the highest anticipated value and n is the alternative appliance, then consumer i's ex ante expected value of information, which determines their demand for information, is:[15]

$$E_i[V_i] = \frac{1}{\phi_i} \ln \left(1 + \exp^{-\phi_i(\widehat{W}_{ik} - (p_m - p_n))} \right) \tag{8}$$

where $\widehat{W}_{ik}$ is the uninformed (or baseline) WTP for product k. According to this model, demand for information is a function of its value: decreasing with absolute relative WTP for the LED at baseline (smaller $|\widehat{W}_{i,k}|$) and increasing with uncertainty over lifetime

[15]See Supplemental C.1 for derivation

operating costs (lower ϕ_i).[16]

Table 2 presents the correlation of WTP for information with both strength of initial preferences for one product over the other and uncertainty about differences in operating costs. In column 1, we regress WTP for information on the absolute value of the baseline relative WTP for the LED and a measure of baseline lifetime cost uncertainty, which we calculate as the standard deviation of baseline beliefs, elicited from the token task. In contrast to the rational model, we find the WTP for information is increasing in the absolute value of baseline WTP for the LED, and decreasing in the consumer's uncertainty. This conclusion is robust to controlling for willingness to accept in the effort task (column 2) as well as measures of risk and time preferences (column 3) and other characteristics of households that might predict demand for information, including 1) the number of sockets and 2) the proportion of the electricity bill the household pays (column 4).[17]

Figure 3 shows that some individuals overvalue information while others undervalue information. The results in Table 2 provide some explanation as to why consumers are not acquiring information optimally: consumers whose product decision is more marginal to information (i.e. those who are more uncertain and more indifferent between the products) do not anticipate this value while consumers whose product decision is not marginal to information have a high WTP for information. Our experimental design enables us to explore whether alternative models incorporating deviations from the basic rational model predict these two findings.

[16] In Appendix Table B13 we demonstrate that, as expected, the revealed value of information in the experiment follows this pattern.

[17] An additional possibility is that ϕ_i in equation 8 also captures the consumers' anticipated attention to new information (which may be incomplete due to behavioral reasons like limited attention, or classical reasons like beliefs about the precision of the information). Consistent with this idea, Fuster et al. (2018) find that WTP for information is higher among those who are ex-ante more certain and that these individuals also place more weight on information provided in their experiment. They argue the negative correlation between prior uncertainty and the choice of attending to information explains why those who are more uncertain have low WTP for information. In contrast, we find no evidence of heterogeneity in attending to information by ex-ante uncertainty. Appendix Figure B6 shows that consumers who are more certain do not place more weight on lifetime cost information. It therefore appears that omitted variable bias, driven by a correlation between uncertainty and preferences for attending to information does not drive the difference between the model predictions and the empirical relationships in Table 2.

4.2.2 Biased Beliefs

We next explore whether bias in prior beliefs could lead to the observed distribution of mistakes in information acquisition. Again, consider the utility function for uninformed individuals as presented in Section 2. If individuals have biased beliefs then the true ex-ante expected value of information differs from the individual's ex-ante expected value of information because ϵ_{ij} has a non-zero mean. Denote $\bar{\epsilon}_{ij}$ as the bias in individual i's beliefs about the energy costs of product j. If $\bar{\epsilon}_{ij} > 0$ then individual i is biased and optimistic about product j (i.e. $\kappa_{ij} \geq k_{ij}$ indicating that true costs are higher than the consumer's beliefs about those costs). If we assume that the error term is still type 1 extreme value random variable with scale parameter ϕ_i but now with mean $\bar{\epsilon}_{ij}$, the true expected value of information for individual i who, when uninformed, prefers product m over the alternative product q is then:

$$E[V_i] = \frac{1}{\phi_i} \ln\left(1 + \exp^{-\phi_i(\widehat{W}_{im} - (p_m - p_q) - (\bar{\epsilon}_{im} - \bar{\epsilon}_{iq}))}\right) \tag{9}$$

Ex ante, the true expected value of information is therefore increasing in the relative bias of the consumer *towards* their ex-ante preferred product (i.e. the product preferred by the uninformed consumer). Intuitively, information is more valuable to consumers if it is more likely to be pivotal - if individuals are biased against their ex-ante preferred product, then correcting this bias is unlikely to change their choices, it will instead reinforce their choice. However, if individuals are biased towards their ex-ante preferred product, i.e. against the alternative, then the bias might be pivotal and they will be more likely to change their mind in response to new information. Biased beliefs could in part explain the failure to acquire information optimally if those who underweight the value of information are biased towards their ex ante preferred product and if those who overweight the value of information are biased against their preferred product.

Our experiment allows us to define individual-level bias in beliefs to test whether it can explain some of the observed distribution of mistakes. Because we elicit a distribution of beliefs from each individual, we can distinguish between bias and uncertainty. We define a consumer as having biased beliefs if the mean of their baseline belief distribution is statistically different at the 95% level to -\$62.50.[18] Figure B7 shows the distribution of mean ex ante beliefs by whether they are biased (53% of the sample) or unbiased (47% of the sample). We separate biased consumers into those who are optimistic about the LED (7% of the sample) and those who are pessimistic about the LED (46% of the sample).[19]

Equation 9 suggests that ex post, information should be more valuable to consumers who have beliefs biased towards their ex ante preferred product: optimists who initially prefer the LED and pessimists initially preferring the halogen. Further, these two groups of consumers should be more likely to undervalue information because the value of correcting their bias would not be reflected in their WTP. Panel (a) of Figure 4 plots the mean probability that a consumer undervalues information by whether they are optimistic, unbiased, or pessimistic about the costs of LEDs both for the group that initially prefers halogens and for the group that initially prefers LEDs. Error bars indicate 95% confidence intervals. Interestingly, optimists, pessimists, and unbiased are equally likely to undervalue information among those who initially prefer LEDs (black bars). Similarly, the three groups are equally likely to undervalue information among those who initially prefer halogens (grey bars). Bias, therefore, does not predict mistakes in information choice. The figure also shows that across the board, initial bulb preference does appear to predict mistakes - consumers with an initial preference for the halogen are more likely to undervalue information.

[18]According to our information treatment, the cost difference between the bulbs would be \$60. A consumer who was certain of this cost would enter all 10 tokens into the range -\$50 to -\$75, which has mid point -\$62.50. Alternative definitions of bias, such as a statistical difference in baseline and endline beliefs, provide similar results.

[19]These measures of bias have some predictive power. Compared to unbiased consumers: on average consumers who are optimistic about the LED are willing to pay \$7 more for the LED package at baseline, while consumers who are pessimistic about the LED are willing to pay \$6 less for the LED package at baseline.

4.2.3 Confirmation Bias and Motivated Reasoning

Having ruled out behavior predicted by rationality or otherwise rational individuals with biased beliefs, we now turn to mental gaps that may be driving the results we see. In particular, two candidate behavioral models that may help explain key features of behavior we observe are confirmation bias and motivated reasoning. These models and empirical evidence on belief formation suggest that information acquisition is affected in a non-Bayesian manner by preferences for information that confirms prior beliefs and/or a preferred state of the world (Epley and Gilovich, 2016; Charness and Dave, 2017; Zimmermann, 2020). Motivated reasoning could be consistent with the fact that WTP for information is higher for those who are more certain in their prior beliefs as these individuals seek out information if they are confident it will align with their beliefs. Further, motivated reasoning is also consistent with WTP for information being higher for those who initially prefer the LED bulb, if these consumers have a strong preference for a state of the world and are therefore more likely to seek out information to affirm their preference.

Panel (b) of Figure 4 provides further suggestive evidence on motivated reasoning as a potential explanation for mistakes in information acquisition. It shows the probability of undervaluing information for consumers based on the political orientation of their county using voting records in the 2020 Presidential Election. In 2019, the Trump administration made headlines for removing regulations on the sale of inefficient light bulbs.[20] It is therefore plausible that individuals evaluate information about the relative efficiency of light bulbs from a political standpoint. Panel (b) of Figure 4 shows the probability of undervaluing information in counties classified into "Democrat" (from a county in the top 20% of the Democratic vote share in the 2020 Presidential election), "Center" (from a county in the middle 20-80th percentiles of the Democratic vote share in the 2020 Presidential election), and "Republican" (from a county in the bottom 20% of

[20] For media coverage of the decision see for example https://www.washingtonpost.com/climate-environment/2019/12/20/trump-administration-just-overturned-ban-old-fashioned-lightbulbs/.

the Democratic vote share in the 2020 Presidential election). We find consumers in strong Republican counties are more likely to undervalue information - the mean share of consumers who undervalue information in Republican counties is statistically different to the mean share of consumers in either Democrat or Center counties at the 5 per cent confidence level. This is consistent with consumers engaging in politically motivated information acquisition that causes them to make costly mistakes.

4.3 Implications for Policy Design

In this section, we derive and compute optimal behavioral policies for addressing imperfect decision making in the presence of mental gaps as functions of reduced-form sufficient statistics (e.g., Mullainathan, Schwartzstein and Congdon, 2012; Allcott and Taubinsky, 2015; Farhi and Gabaix, 2020). In the previous section, we showed suggestive evidence that motivated reasoning or confirmation bias are mental gaps that are in line with the results we observe. However, the strength of the sufficient statistics approach is that to derive optimal policy and assess its impacts, it is sufficient to identify the impact of mental gaps on decision making (i.e. the internality), as our experiment is designed to do. It is not necessary to know the specific mechanisms driving mistakes in behavior.

4.3.1 Optimal Policy Interventions

In what follows, we consider two policy scenarios. First, we consider an approach where a planner chooses a single subsidy level to encourage consumers to view information when purchasing a product. Then we look at a more traditional approach where the planner offers a single subsidy level to encourage the purchase of the more efficient product. A subsidy for viewing information is increasingly applicable given that many purchasing decisions are being made online, making it possible to offer subsidies for viewing information screens and tutorials. As an example, in 2020 the Australian state of Victoria established a $50 incentive for customers to view competing electricity contracts on their price comparison website.

Following the notation above, ν_{ij} is consumer i's valuation of the light bulb $j \in \{0, 1\}$, κ_{ij} is the lifetime operating costs for i of bulb j and p_j is the price of bulb j. For simplicity, we fix the value and lifetime operating costs of the inefficient bulb to be the same across consumers $\nu_{i0} = \nu_0$ and $\kappa_{i0} = \kappa_0$ while allowing them to vary for the efficient bulb. For notational convenience, we also drop subscripts i such that the consumer's unbiased relative WTP for the efficient bulb is $W_1 = (\nu_1 - \kappa_1) - (\nu_0 - \kappa_0)$ and $\widehat{W_1}$ is their biased or uninformed relative WTP for the efficient bulb. We denote $F_X(x)$ the cumulative density function (CDF) of variable X[21] and $f_X(x)$ its probability density function (PDF). Then define the following: $Z(s^I)$ is the consumer's budget given subsidy s^I[22], $D_B(p^I) = 1 - F_{W^I}(p^I)$ is the biased demand curve of information, and $\tilde{V} = V - e$ is the value of information net of effort cost.

The welfare from subsidy s^I at price of information p^I can be written:

$$\mu(s^I) = Z(s^I) + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq (p_1 - p_0)} (W_1 - (p_1 - p_0)) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1) d\widehat{W_1} dW_1$$
$$+ \int_{W^I > p^I - s^I} (\tilde{V} - p^I + s^I) f_{W^I, \tilde{V}}(W^I, \tilde{V}) dW^I d\tilde{V} \tag{10}$$

where $\nu_0 - p_0 - \kappa_0$ accounts for the utility of choosing the inefficient product, the first integral accounts for the incremental utility of choosing the efficient product when uninformed, and the second integral accounts for the utility of acquiring information. Taking the derivative of this expression with respect to the subsidy s^I gives first order condition:[23]

$$\mu'(s^I) = (s^I - A(s^I)) D'_B(s^I) \tag{11}$$

where $A(s^I) = E_{\tilde{V}|W^I}\left(B|\tilde{V} - B = p^I - s^I\right)$ is the average marginal bias in information acquisition at subsidy s^I, and $B = V - W^I - e$. The information subsidy improves welfare if the average gain from improved product choices outweighs the average additional effort

[21] So, for example, $F_{W^I}(p^I)$ is the probability that the WTP for information W^I is less than the price of information p^I

[22] We assume the subsidy is revenue neutral and the government can levy non-distortionary lump sums.

[23] See Supplemental C.2 for derivation

costs from the consumers whose information choice is marginal to the subsidy. The optimal subsidy balances this trade off at the margin such that the payment is equal to consumers' average marginal bias $s^{I*} = A(-s^{I*})$.

We compare this information subsidy to a more conventional product subsidy for encouraging take up of more efficient products. Analogous to the information subsidy, the optimal product subsidy equates the average marginal bias in product choice with the payment (Allcott and Taubinsky, 2015). The product subsidy improves welfare if the utility gain experienced by marginal consumers who truly value LEDs more than their marginal cost but are biased, outweighs any loss from distorting the product choice of other marginal consumers (the classic Harberger distortion (Harberger, 1964)). Whether a product or information subsidy is preferred depends on the benefit from improved product choices for each optimal instrument versus any losses from either distorted product choices or mental effort and therefore will be context specific.[24]

Our experiment is designed to recover the sufficient statistics necessary to calculate the optimal information and product subsidies and compare their welfare effects in the context of appliance purchasing behavior. We begin with the optimal information subsidy. As with similar studies, we initially assume that the information provision is a "pure nudge" so that consumers' informed demand revealed in our experiment is the "true" unbiased demand (e.g., Allcott and Taubinsky, 2015). We perform robustness tests of our welfare ranking of the two policies when we relax this assumption.

To estimate the average marginal information acquisition bias we need an estimate of individual effort costs. As previously discussed, consumers' revealed willingness to accept for the effort task in the experiment (W^e) appears to be a good proxy for true effort cost (e). Therefore, we assume that true effort cost is a function of the experimental proxy: $e = f(W^e)$, where $\frac{\partial W^I}{\partial f(W^e)} = -1$, i.e. an additional dollar of effort cost reduces WTP for information by exactly \$1. Assuming a linear function for f we can then compute effort costs e by estimating a linear regression of W^I on W^e and computing $\hat{e} = -\widehat{\beta}_1 \times W^e$.

[24]In Appendix C.3 we formalize the intuition behind the comparison between the two subsidies.

To compute the optimal subsidy we estimate the average marginal bias at each discrete level of W^I offered in the experiment as follows:

$$B = \sum_{n=1}^{N} \tau_n \mathbf{1}\left[W^I = w_n\right] + \rho \tag{12}$$

The parameters τ_n measure the average marginal bias for those who were willing to pay w_n for information and ρ is an idiosyncratic error term.

Figure 5 plots the estimated average marginal bias in information provision and 95% confidence intervals according to Equation (12) with effort costs estimated as above. At most levels of WTP for information the average marginal bias is positive (i.e. consumers underweight the value of information). The exception are the consumers stating a WTP above \$10 for information. This group of consumers overweight the value of information.

We compute the optimal information subsidy for those marginal to subsidies in our experiment by incrementing the subsidy according to the discrete levels of the information prices offered in the experiment, from an assumed initial price of zero–as if the information were already free.[25] Likewise, we assume that the baseline relative price of the bulb packages is zero (i.e. the packages have the same market price). If the baseline price of information is zero, a proportion of consumers with WTP for information ≥ 0 will be informed in the absence of a subsidy. With these assumptions, in the absence of subsidies, 86% of consumers are informed, and 88% of consumers purchase the LED.

Panel A of Table 3 reports the results of computing the change in welfare from incremental increases in the information subsidy from an initial price of zero. Column (1) reports the subsidy level corresponding to what was offered in the experiment. Column (2) reports the average marginal bias at each subsidy level. Column (3) reports the incremental increase in the proportion of consumers that become informed from a particular subsidy level relative to the previous level, or in the case of the first row, relative to zero. Column (4) reports the change in welfare due to the incremental change in the subsidy

[25]This is consistent with the assumption that the social marginal cost of information provision is zero, or close to it.

(relative to the previous row or zero) and column (5) reports the cumulative welfare effect of a particular subsidy, summing across the incremental changes in Column (4).[26] The subsidy should be increased so long as the welfare effects of the incremental change are positive. We find an information subsidy of approximately \$8.75 maximizes welfare among these consumers.[27]

We now consider the welfare gain from a standard product subsidy to purchase more efficient LED bulbs. The columns of Panel B Table 3 mimic those of Panel A, with the exception of column (3) which reports the change in the share of consumers opting for the LED.[28] The average marginal bias in column (2) is the difference between the biased demand for LED, due to lack of information, and the unbiased demand at each subsidized price. Assuming the information acts as a "pure nudge," our estimate of bias is the treatment effect of information on demand for the LED at increments of baseline WTP for the LED. We estimate this treatment effect using the random information cost draw as an instrument for viewing information. We find a product subsidy of \$1.875 increases welfare and welfare is further increased at a product subsidy of \$12.1875 however further increases in the subsidy are not welfare improving (the average marginal bias at a subsidy of \$26.25 is \$7.056). The optimal product subsidy is therefore approximately \$12. For an LED package cost of \$20 this represents a 60% subsidy.

To evaluate whether information subsidies dominate product subsidies we then compare the cumulative change in welfare at each optimal subsidy (i.e. column (6) of Table 3). The optimal information subsidy increases welfare by 0.93, while the optimal product subsidy increases welfare by 0.854. In our setting the information subsidy therefore dominates the product subsidy. The change in welfare from the information subsidy is 35% of

[26]The change in welfare from a change in the subsidy can be computed as the change in market share from the subsidy increase (Column (3) of Table 3) multiplied by the sum of the average marginal bias (Column (2) of Table 3) and the average WTP for marginal consumers (Allcott and Taubinsky, 2015).

[27]This information subsidy is a lower bound of the optimal subsidy. Further increases in the subsidy may improve welfare depending on the bias of consumers who are marginal to larger subsidies. We do not observe this average marginal bias as their WTP for information was below the largest subsidy offered in the experiment.

[28]Due to limited sample size, we group consumers with relative WTP for the LED between -5.625 and -18.75 and assign them WTP -12.1875.

the aggregate welfare cost of biased information acquisition. The change in welfare from the product subsidy is 7% of the aggregate welfare cost of biased product choice. This suggests that the non-traditional policy instrument we propose, information subsidies, can potentially target welfare improvements more effectively than conventional product subsidies.

4.3.2 Sensitivity Analysis

We next explore the sensitivity of our policy results to our assumption that our information provision is a "pure nudge." It is possible that the intervention does not eliminate all biases in light bulb product choice. For example, it could be that information corrects beliefs but does not eliminate inattention. We, therefore, consider a scenario where, rather than a "pure nudge," the information intervention is a "nudge in the right direction." That is, the nudge pushes consumers closer to their true valuation, but does not fully debias them. To explore what this does to the welfare ranking of our two policies we assume that policy is designed based on the mismeasured estimates of bias, while actual welfare depends on true experienced utility that is not observed by the policy maker. We consider three levels of this experienced utility: low, i.e. for each consumer, the true change in WTP for the LED due to information is 10% higher than observed in our experiment, medium, i.e. the true change is 30% higher than we observe, and high, i.e. the true change is 50% higher.

Table B14 shows that at all three levels of mismeasurement, the information subsidy continues to dominate the product subsidy for the "nudge in the right direction" and welfare is higher than the baseline. The relative benefit of the information subsidy over the product subsidy is lower than when the nudge is pure. Information eliminates biased product choice under a "pure nudge", but it only improves product choice under a "nudge in the right direction". In contrast, the product subsidy does not rely on eliminating bias, but rather directly corrects product choice through changing product prices. As the subsidy is the same consumers make the same biased choices, but correcting those choices results in higher welfare gains.

We explore the sensitivity of the welfare ranking of the two policies to the demand curves used. It could be that bias would be different for another population of consumers. For this exercise, we go back to assuming that information serves as a "pure nudge," but consider what would happen if the change in WTP recovered by an experiment similar to ours were 10%, 30%, or 50% higher. To recalculate optimal subsidies, we retain consumers' baseline WTP for the LED, and their WTP for information and adjust their endline WTP for the LED (and therefore the revealed value of information) according to the three scenarios described above. We then recompute the average marginal biases in product and information space and recalculate optimal product and information subsidies.

Appendix Table B15 summarizes the optimal subsidy, product and information choices, and associated welfare from this exercise. In each case, we find that the level of optimal product and information subsidies are unchanged from the base case, but the welfare impacts of the subsidies are larger reflecting the larger bias that these subsidies address.[29] We also find that the information subsidy dominates the product subsidy in all cases. Further, the relative welfare gain from the information subsidy (difference in welfare between the information and product subsidy) is higher than the base case for all three scenarios.

5 Conclusion

In a world saturated with information, consumers are often poorly informed and consequently routinely make mistakes. In this paper, we outlined an experiment designed to test whether remaining uninformed is the result of frictions in information acquisition, or mental gaps in decision making. The test is based on comparing ex ante WTP for information with the revealed value of this information ex post.

[29]The optimal information subsidy already informed all consumers at a lower level of bias hence increasing the bias cannot result in a higher subsidy. The optimal product subsidy does not increase in part because the price increments at which we can measure bias in the experiment are relatively lumpy, and the fact that the average marginal bias in product choice is non monotonic and declines past a subsidy level of approximately $12.

We implemented this experiment in the context of appliance choice where mental gaps in information acquisition about operating costs may be an important driver of investment inefficiencies. We found both under and over weighting of the value of information on energy efficiency and durability of the goods, evidence that consumers do not optimally trade off the costs and benefits of acquiring and processing information.

We consider whether competing decision models are consistent with the observed behavior in our experiment. First, we show that consumers' behavior is inconsistent with the rational model's prediction that consumers' WTP for information is correlated with the degree of uncertainty and the strength of their initial preference. Then, using an individual-level measure of bias, we demonstrate behavior is also inconsistent with otherwise rational consumers acquiring information suboptimally due to biased beliefs. Rather, the observed behavior is more consistent with mental gap models that incorporate confirmation bias and motivated reasoning.

If consumers are not optimizing subject to frictions, paying decision makers to acquire information may improve welfare. We derive the optimal information subsidy in the presence of mental gaps and compute it using our experimental data. In our setting, it is optimal to pay consumers close to $9 to acquire information. We then compare welfare under this subsidy with welfare under the optimal product subsidy of around $12. We find that the information subsidy dominates the product subsidy in our context. More generally, we show that the choice between policy interventions depends on the benefit from improved product choices for each optimal instrument versus any losses from either distorted product choices (in the case of the product subsidy) or mental effort (in the case of the information subsidy).

Governments frequently intervene to make information more readily accessible to decision makers. For example, governments mandate that appliance manufacturers provide energy cost information to consumers in a standardized format. Governments also frequently intervene in product markets by providing direct subsidies. We demonstrate that a non-traditional policy instrument, information subsidies have the potential to target welfare improvements more effectively than conventional product subsidies. In a world where decisions are taken and information is delivered online, paying for attention could therefore result in substantial welfare gains in a wide variety of settings.

References

Allcott, Hunt, and Dmitry Taubinsky. 2015. "Evaluating behaviorally motivated policy: experimental evidence from the lightbulb market." *American Economic Review*, 105(8): 2501–2538.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky. 2019. "Regressive sin taxes, with an application to the optimal soda tax." *Quarterly Journal of Economics*, 134(3): 1557–1626.

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. 2014. "Energy Policy with Externalities and Internalities." *Journal of Public Economics*, 112(April): 72–88.

Baldwin, S, G Bindewald, A Brown, C Chen, K Cheung, C Clark, J Cresko, M Crozat, J Daniels, J Edmonds, et al. 2015. "Quadrennial technology review: An assessment of energy technologies and research Opportunities." Technical Report.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka. 2016. "Attention discrimination: Theory and field experiments with monitoring information acquisition." *American Economic Review*, 106(6): 1437–75.

Beattie, Graham, Iza Ding, and Andrea La Nauze. 2022. "Is there an energy efficiency gap in China? Evidence from an information experiment." *Journal of Environmental Economics and Management*, 115: 102713.

Bénabou, Roland, and Jean Tirole. 2002. "Self-confidence and personal motivation." *Quarterly Journal of Economics*, 117(3): 871–915.

Bernheim, B Douglas, and Antonio Rangel. 2009. "Beyond revealed preference: choice-theoretic foundations for behavioral welfare economics." *Quarterly Journal of Economics*, 124(1): 51–104.

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor. 2017. "Choose to lose: Health plan choices from a menu with dominated option." *Quarterly Journal of Economics*, 132(3): 1319–1372.

Bronchetti, Erin T, Judd B. Kessler, Ellen B. Magenheim, Dmitry Taubinsky, and Eric Zwick. 2022. "Is Attention Produced Optimally? Theory and Evidence from Experiments with Bandwidth Enhancements." *Forthcoming, Econometrica.*

Bronnenberg, Bart J, Jean-Pierre Dubé, Matthew Gentzkow, and Jesse M Shapiro. 2015. "Do pharmacists buy Bayer? Informed shoppers and the brand premium." *Quarterly Journal of Economics*, 130(4): 1669–1726.

Caplin, Andrew, and Mark Dean. 2015. "Revealed preference, rational inattention, and costly information acquisition." *American Economic Review*, 105(7): 2183–2203.

Caplin, Andrew, Mark Dean, and Daniel Martin. 2011. "Search and satisficing." *American Economic Review*, 101(7): 2899–2922.

Charness, Gary, and Chetan Dave. 2017. "Confirmation bias with motivated beliefs." *Games and Economic Behavior*, 104: 1–23.

Choi, James J, David Laibson, and Brigitte C Madrian. 2010. "Why does the law of one price fail? An experiment on index mutual funds." *Review of Financial Studies*, 23(4): 1405–1432.

Davis, Lucas, and Gilbert Metcalf. 2015. "Does Better Information Lead to Better Choices? Evidence from Energy-Efficiency Labels." *Journal of the Association of Environmental and Resource Economists*, 3(3): 589–625.

Dean, Mark, and Nate Leigh Neligh. 2018. "Experimental tests of rational inattention."

Delavande, Adeline, and Hans-Peter Kohler. 2009. "Subjective expectations in the context of HIV/AIDS in Malawi." *Demographic Research*, 20: 817.

Epley, Nicholas, and Thomas Gilovich. 2016. "The mechanics of motivated reasoning." *Journal of Economic Perspectives*, 30(3): 133–40.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde. 2018. "Global evidence on economic preferences." *Quarterly Journal of Economics*, 133(4): 1645–1692.

Falk, Armin, Anke Becker, Thomas J Dohmen, David Huffman, and Uwe Sunde. 2016. "The preference survey module: A validated instrument for measuring risk, time, and social preferences." *IZA Discussion Paper No. 9674.*

Farhi, Emmanuel, and Xavier Gabaix. 2020. "Optimal Taxation with Behavioral Agents." *American Economic Review*, 110(1): 298–336.

Fuster, Andreas, Ricardo Perez-Truglia, Mirko Wiederholt, and Basit Zafar. 2018. "Expectations with endogenous information acquisition: An experimental investigation." *Review of Economics and Statistics*, 1–54.

Gabaix, Xavier. 2014. "A sparsity-based model of bounded rationality." *Quarterly Journal of Economics*, 129(4): 1661–1710.

Gabaix, Xavier. 2019. "Behavioral inattention." In *Handbook of Behavioral Economics: Applications and Foundations 1.* Vol. 2, 261–343. Elsevier.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg. 2006. "Costly information acquisition: Experimental analysis of a boundedly rational model." *American Economic Review*, 96(4): 1043–1068.

Handel, Benjamin, and Joshua Schwartzstein. 2018. "Frictions or mental gaps: what's behind the information we (don't) use and when do we care?" *Journal of Economic Perspectives*, 32(1): 155–78.

Handel, Benjamin R. 2013. "Adverse selection and inertia in health insurance markets: When nudging hurts." *American Economic Review*, 103(7): 2643–82.

Handel, Benjamin R, and Jonathan T Kolstad. 2015. "Health insurance for "humans": Information frictions, plan choice, and consumer welfare." *American Economic Review*, 105(8): 2449–2500.

Handel, Benjamin R, Jonathan T Kolstad, and Johannes Spinnewijn. 2019. "Information frictions and adverse selection: Policy interventions in health insurance markets." *Review of Economics and Statistics*, 101(2): 326–340.

Harberger, Arnold C. 1964. "The measurement of waste." *American Economic Review*, 54(3): 58–76.

Ho, Daniel E, Zoe C Ashwood, and Cassandra Handan-Nader. 2019. "New Evidence on Information Disclosure through Restaurant Hygiene Grading: Reply." *American Economic Journal: Economic Policy*, 11(4): 404–428.

Hoopes, Jeffrey L, Daniel H Reck, and Joel Slemrod. 2015. "Taxpayer search for information: Implications for rational attention." *American Economic Journal: Economic Policy*, 7(3): 177–208.

Hortaçsu, Ali, and Chad Syverson. 2004. "Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds." *Quarterly Journal of Economics*, 119(2): 403–456.

Houde, Sébastien, and Erica Myers. 2019. "Heterogeneous (mis-) perceptions of energy costs: Implications for measurement and policy design." National Bureau of Economic Research.

Howard, Greg. 2022. "A Check for Rational Inattention." *working paper*.

Khaw, Mel Win, Luminita Stevens, and Michael Woodford. 2017. "Discrete adjustment to a changing environment: Experimental evidence." *Journal of Monetary Economics*, 91: 88–103.

Kunda, Ziva. 1990. "The case for motivated reasoning." *Psychological Bulletin*, 108(3): 480.

List, John, Matthias Rodemeier, Sutanuka Roy, Gregory Sun, et al. 2022. "Judging Nudging: Toward an Understanding of the Welfare Effects of Nudges Versus Taxes." The Field Experiments Website.

Loewenstein, George, Cass R Sunstein, and Russell Golman. 2014. "Disclosure: Psychology changes everything." *Annual Review of Economics*, 6(1): 391–419.

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt. 2021. "Rational inattention: A review."

Mullainathan, Sendhil, Joshua Schwartzstein, and William J Congdon. 2012. "A reduced-form approach to behavioral public finance." *Annu. Rev. Econ.*, 4(1): 511–540.

Sallee, James M. 2014. "Rational Inattention and Energy Efficiency." *Journal of Law and Economics*, 57.

Schwartzstein, Joshua. 2014. "Selective attention and learning." *Journal of the European Economic Association*, 12(6): 1423–1452.

Serra-Garcia, Marta, and Nora Szech. 2022. "The (in) elasticity of moral ignorance." *Management Science*, 68(7): 4815–4834.

Shrestha, Maheshwor. 2020. "Get rich or die tryin': Perceived earnings, perceived mortality rates, and migration decisions of potential work migrants from Nepal." *World Bank Economic Review*, 34(1): 1–27.

Sims, Christopher A. 2003. "Implications of rational inattention." *Journal of Monetary Economics*, 50(3): 665–690.

Taubinsky, Dmitry, and Alex Rees-Jones. 2018. "Attention Variation and Welfare: Theory and Evidence from a Tax Salience Experiment." *Review of Economic Studies*, 85(4): 2462–2496.

Winston, Clifford. 2008. "The Efficacy of information policy: A review of Archon Fung, Mary Graham, and David Weil's full disclosure: The perils and promise of transparency." *Journal of Economic Literature*, 46(3): 704–17.

Woodford, Michael. 2012. "Inattentive valuation and reference-dependent choice."

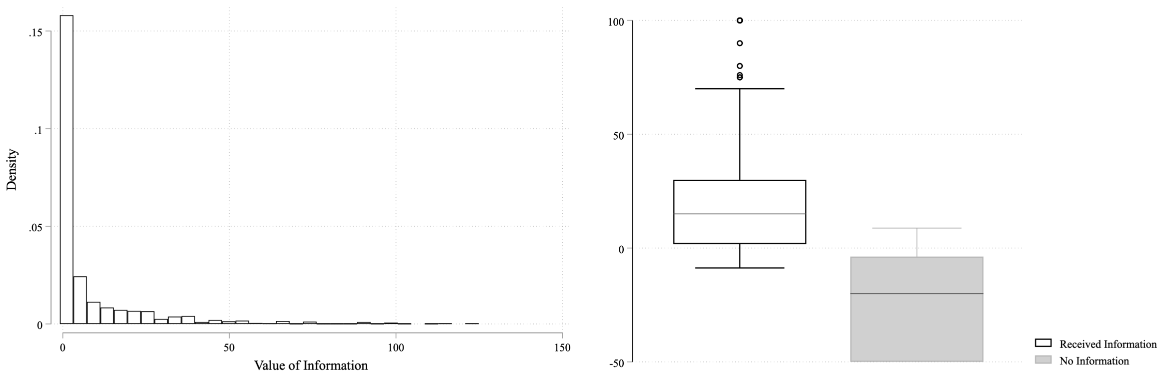
Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data.* MIT press.

Zimmermann, Florian. 2020. "The dynamics of motivated beliefs." *American Economic Review*, 110(2): 337–61.

6 Figures

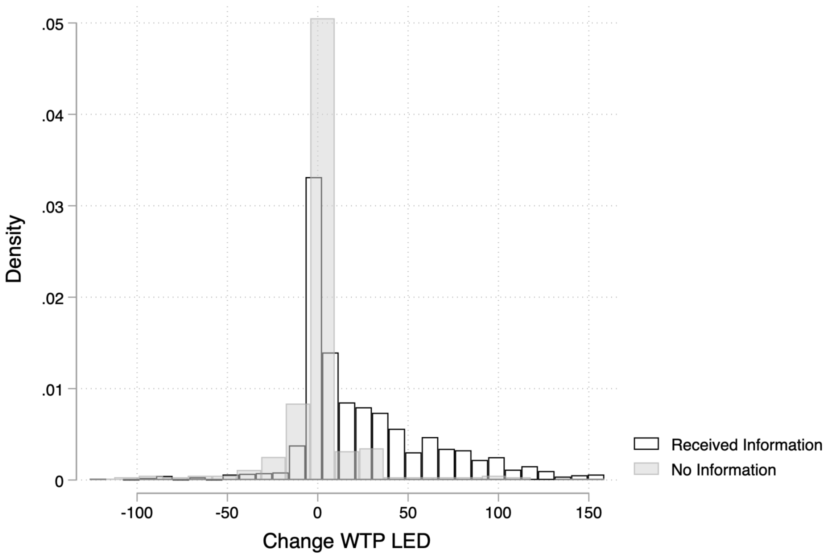
Figure 1: Distributions of Value of Information and Willingness to Pay for Information

(a) Value of Information (b) Willingness to Pay



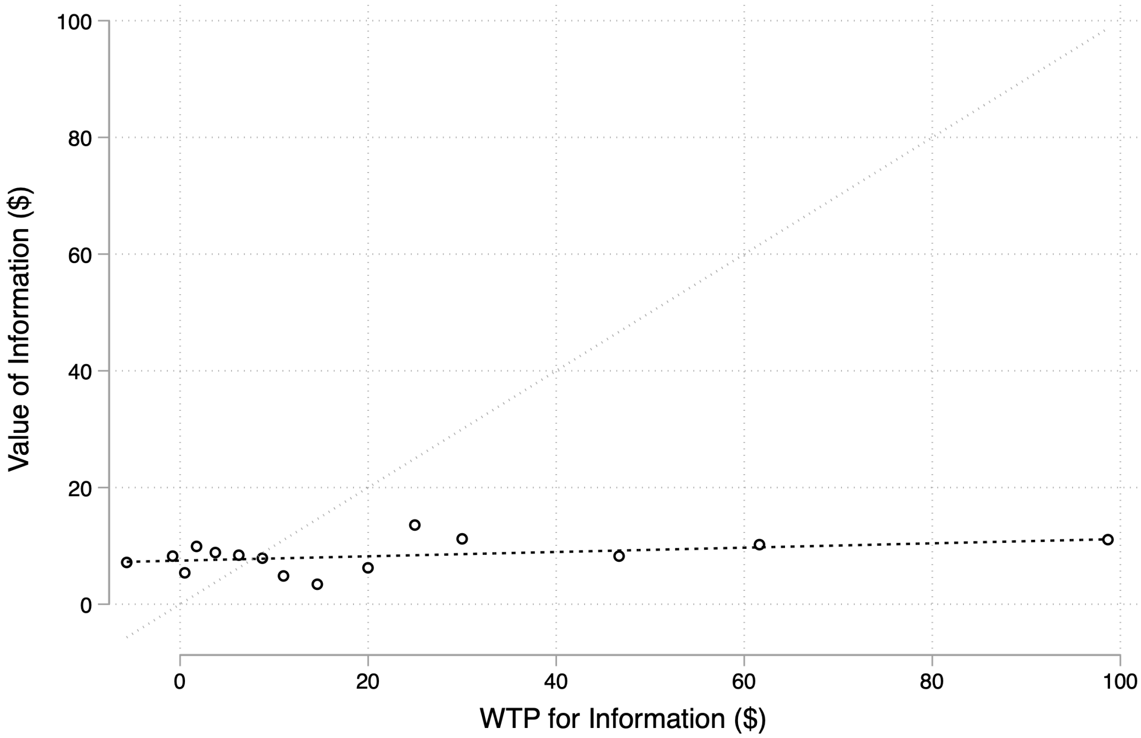
Notes: Panel (a) is a histogram of computed value of information revealed by changes in product choice for those receiving information in the experiment. Panel (b) is a box plot of willingness to pay for information on lifetime costs of bulbs for those receiving information in the experiment and those not receiving information in the experiment.

Figure 2: Distribution of Difference in Willingness to Pay for the LED Between Baseline and Endline by Information Group



Notes: Histogram of difference (Endline - Baseline) in relative willingness to pay for LED for those receiving information on lifetime costs of bulbs and those not receiving information in the experiment. Baseline is prior to information choice. Endline is after information choice.

Figure 3: Willingness to Pay for Information and Value of Information

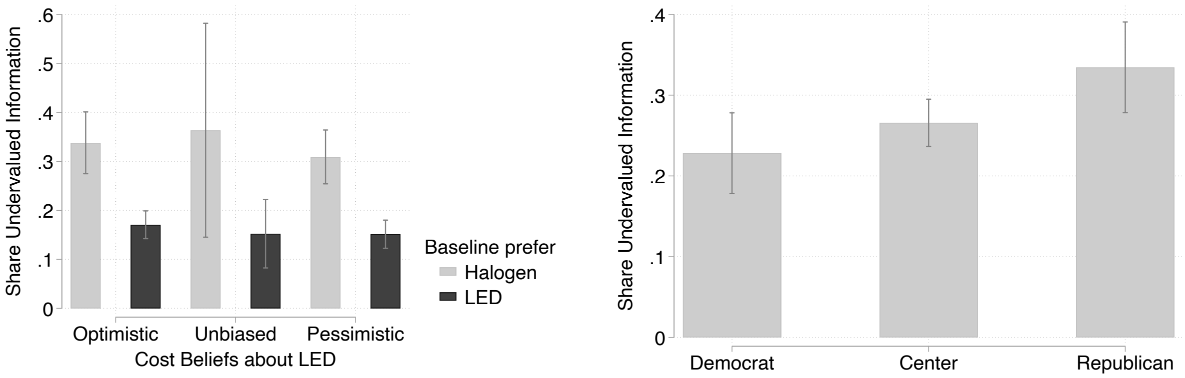


Notes: Figure shows a binned scatter plot of revealed value of information vs WTP for information. WTP is Willingness to Pay.

Figure 4: Biased Beliefs, Political Motivations and Mistakes in Information Acquisition

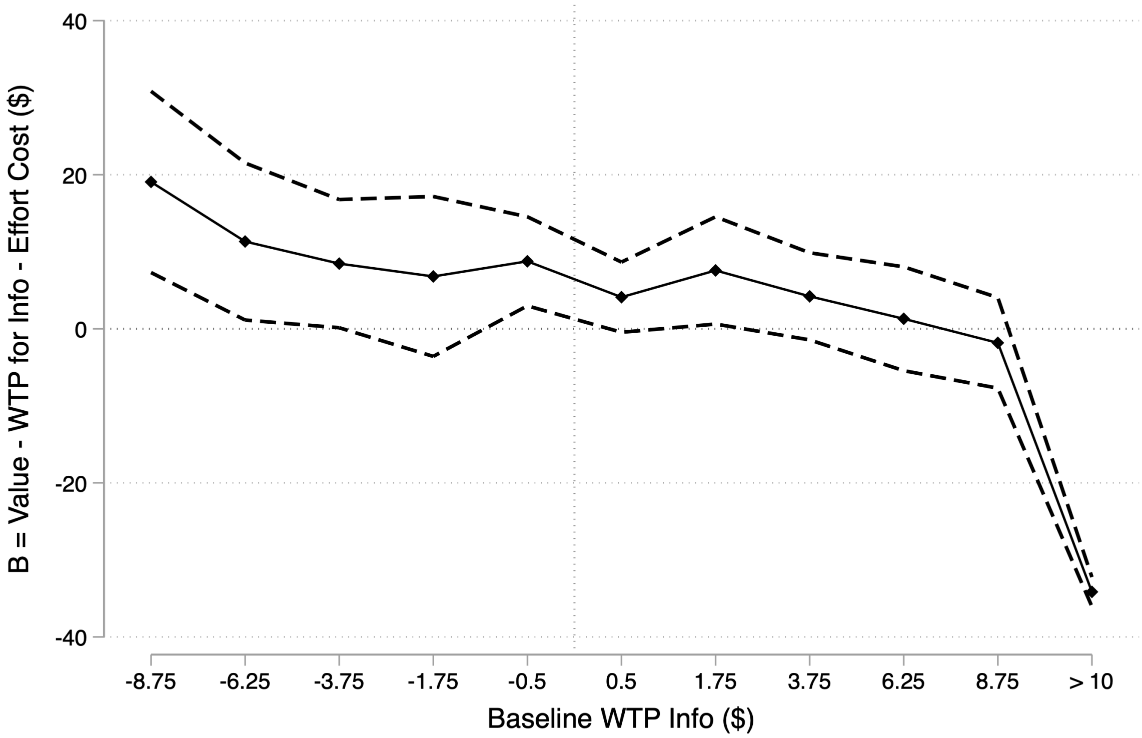
(a) Beliefs, preferences and undervaluation

(b) Political motivations



Notes: Panel (a) plots the probability a consumer undervalues information within categories defined by biased beliefs and initial bulb preference. Bias is evaluated for each consumer based on a test that the mean of the distribution of their beliefs is equal to -\$62.50 (the information provided in the experiment). Optimists are biased and have mean belief $< -\$62.50$, pessimists are biased and have mean belief $> -\$62.50$. Negative values indicate belief that the LED would cost less. Panel (b) plots the probability a consumer undervalues information in the following categories: "Democrat" (from a county in the top 20% of the Democratic vote share in the 2020 Presidential election), "Center" (from a county in the middle 21-79th percentiles of the Democratic vote share in the 2020 Presidential election), and "Republican" (from a county in the bottom 20% of the Democratic vote share in the 2020 Presidential election).

Figure 5: Average Marginal Bias in Information Acquisition



Notes: Figure plots point estimates and 95% confidence intervals for average marginal bias in information acquisition at each level of baseline willingness to pay for information. WTP is Willingness to Pay. Baseline is prior to information choice.

7 Tables

Table 1: Information Acquisition

	Dependent Variable = Value of Information			
Samples:	Info	Info	Marginal (a)	Marginal (a)+(b)
	(1)	(2)	(3)	(4)
(a) WTP Info	0.037**	0.039**	0.059	0.062
	(0.019)	(0.019)	(0.156)	(0.214)
(b) WTA Effort		-0.011	-0.007	0.310
		(0.016)	(0.022)	(0.429)
Constant	7.469***	7.629***	7.677***	7.707***
	(0.571)	(0.635)	(0.810)	(1.093)
Observations	1435	1435	644	440
Test optimal acquisition				
F-statistic (a) = 1	2697.41	2683.27	36.31	19.14

Notes: Table shows results of regressing the revealed value of information (Value of Information) on willingness to pay for information (WTP Info) and willingness to accept to undertake the experimental effort task (WTA Effort). Info Sample is the sample that viewed information. Marginal Samples are samples that were marginal to prices in the price lists (i.e. with WTP/WTA within the range of prices offered in the experiment to view information or undertake the effort task). Observations are weighted using probability weights to account for the probability of treatment. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. F statistic (a) reports the test statistic for the null hypothesis that the coefficient on WTP Info (row (a)) is equal to one (necessary for optimal information acquisition).

Table 2: Testing Predictions of Rational Model of Information Acquisition

	Dependent Variable = WTP Info			
	(1)	(2)	(3)	(4)
| Baseline WTP LED |	0.065**	0.070**	0.074**	0.071**
	(0.031)	(0.031)	(0.031)	(0.031)
Baseline Cost Uncertainty	-0.067**	-0.065**	-0.055*	-0.050
	(0.031)	(0.031)	(0.031)	(0.032)
WTA Effort		-0.054	-0.048	-0.046
		(0.033)	(0.033)	(0.033)
Patience			0.261***	0.237***
			(0.072)	(0.074)
Risk Tolerance			-0.352**	-0.362***
			(0.140)	(0.140)
Sockets				0.090
				(0.071)
Pays Electricity Bills				4.132
				(2.851)
Observations	1902	1902	1901	1901

Notes: Table shows results of regressing willingness to pay for information (WTP Info) on: the absolute value of willingness to pay for the LED before information was offered (\| Baseline WTP LED \|), the standard deviation of beliefs about relative costs of LED bulbs over 10 years before information was offered (Baseline Cost Uncertainty), willingness to accept to undertake the experimental effort task (WTA Effort), a measure of patience (Patience) and risk preference (Risk Tolerance) elicited via the staircase procedures of Falk et al. (2016), the number of lightbulb sockets in a consumer's home (Sockets) and a binary indicator for whether a consumer pays their electricity bills (Pays Electricity Bills).

Table 3: Welfare from Information and Product Subsidies

Panel A: Information Subsidy

	Subsidy	Bias	Δ Info(%)	Δ Welfare	Cum Δ Welfare
(1)	1.75	6.795	.079	.47	.47
(2)	3.75	8.458	.029	.167	.637
(3)	6.25	11.33	.02	.124	.761
(4)	8.75	19.069	.015	.169	.93

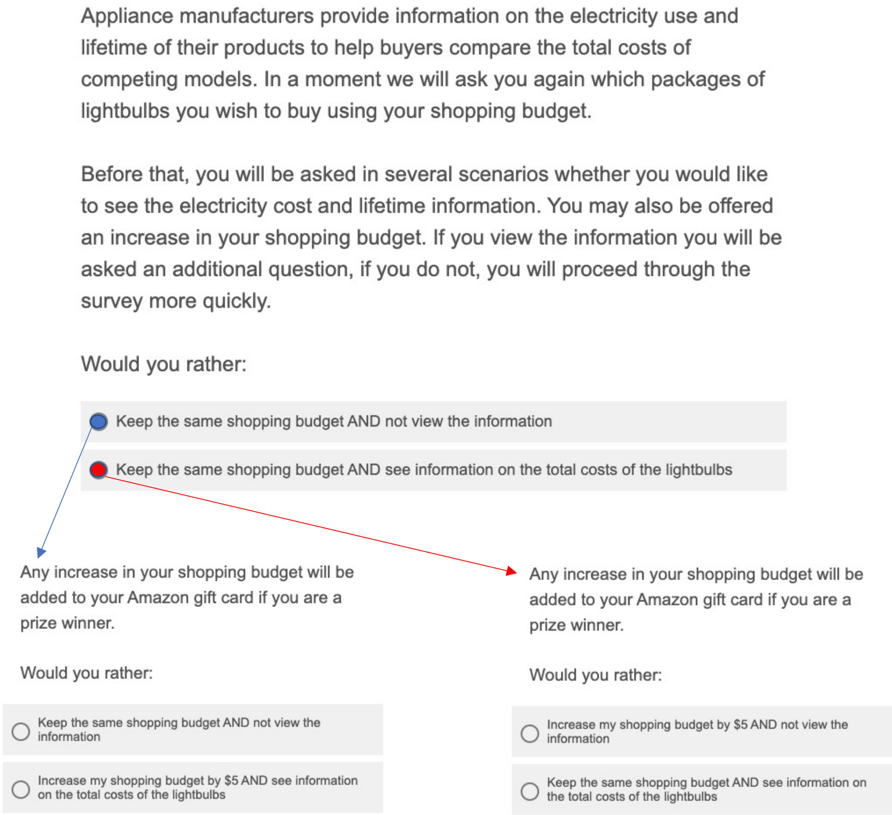
Panel B: Product Subsidy

	Subsidy	Bias	Δ LED(%)	Δ Welfare	Cum Δ Welfare
(1)	1.875	9.556	.044	.378	.378
(2)	12.1875	25.481	.026	.476	.854
(3)	26.25	7.056	.04	-.483	.371
(4)	33.75	-21.176	.01	-.499	-.128

Notes: Table reports welfare analysis for information and product subsidies. In Panel A Bias is the Average Marginal Bias in information acquisition. In Panel B Bias is the Average Marginal Bias in product choice. In Panel A Δ Info (%) is the change in the share of consumers that are informed at the information subsidy in column (1). In both panels, Δ Welfare is the net welfare gain from incrementing the subsidy and Cum Δ Welfare is the running sum of Δ Welfare. In Panel B Δ LED (%) is the change in the share of consumers choosing the LED given the subsidy to the LED package in column (1). All calculations assume consumers with willingness to pay for information above zero are informed without any subsidy and that the unsubsidized relative price of bulb packages is zero.

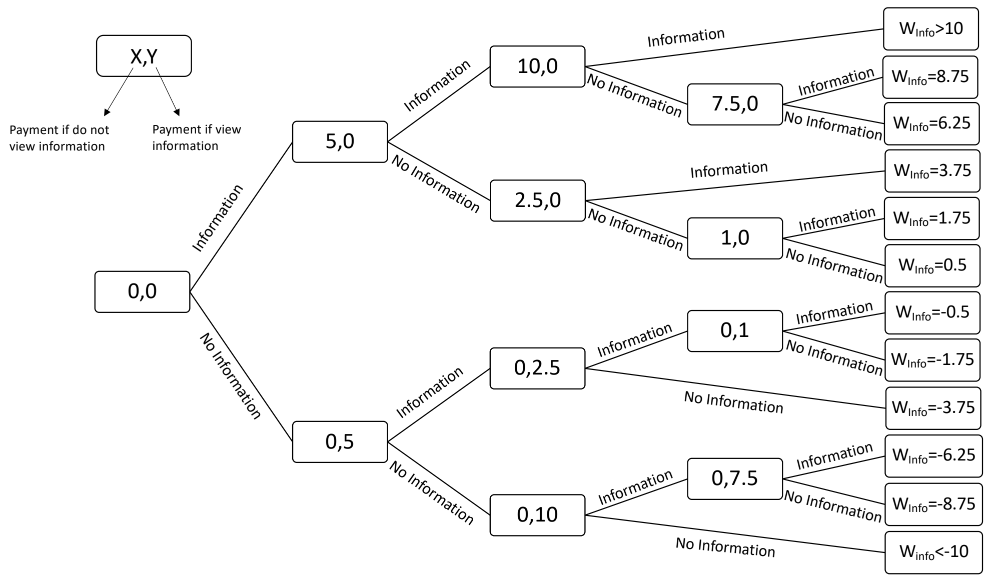
A Supplemental: Experiment Details

Figure A1: Elicitation of Willingness to Pay for Information



Notes: Figure shows screen shots of the experimental module designed to elicit consumer willingness to pay for information on lifetime operating costs of light bulbs. If at the first question in the module, consumers answered they would rather not view information (blue dot) they were then asked if they would like to view the information and increase their shopping budget by $5. If they answer that they would like to view information at the first question (red dot) they were asked if they would like to not view the information and increase their shopping budget by $5. Depending on their answers they were directed through the staircase to identify their switching point. For the full staircase see Appendix A2.

Figure A2: Staircase to Elicit Willingness to Pay for Information



Notes: The staircase procedure works as follows. First, each respondent is asked whether they would like to keep the same shopping budget and view the information on the lifetime costs of light bulbs. If they choose the information, they are then asked if they would like to view the information and keep the same shopping budget, or increase their shopping budget by $5 and not view the information. If they had instead chosen not to view the information, they would be asked whether they would like to increase their shopping budget by $5 and view the information, or keep the same shopping budget and not view the information. The respondent is then asked the remaining questions depending on their path through the staircase.

Figure A3: Information Treatment

Below is some information on the lifetime costs of buying and using lightbulbs.

Please review this information and answer the question below.

LED lightbulbs last longer than halogen lightbulbs. At average use, halogen lightbulbs need to be replaced at least every 11 months while LED lightbulbs need to be replaced every thirteen years. If halogens and LEDs each cost $2 per bulb this means that the total purchase prices for ten years of lightbulbs are:

- $22 for halogen bulbs
- $2 for LED bulbs

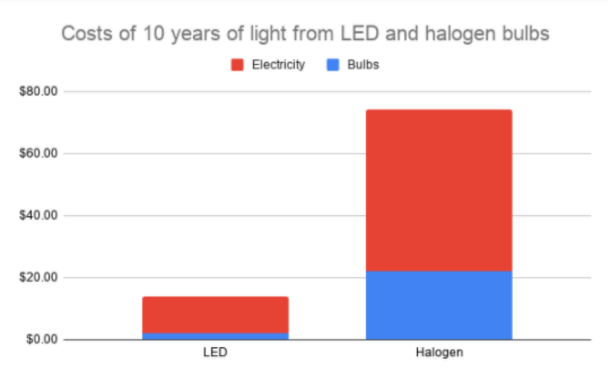
LED bulbs use less electricity than halogen bulbs. At national average usage and electricity prices:

- A 43 Watt halogen uses $5.20 in electricity each year
- An equivalent LED uses $1.20 in electricity each year

For ten years of light, the total costs to purchase bulbs and electricity would be:

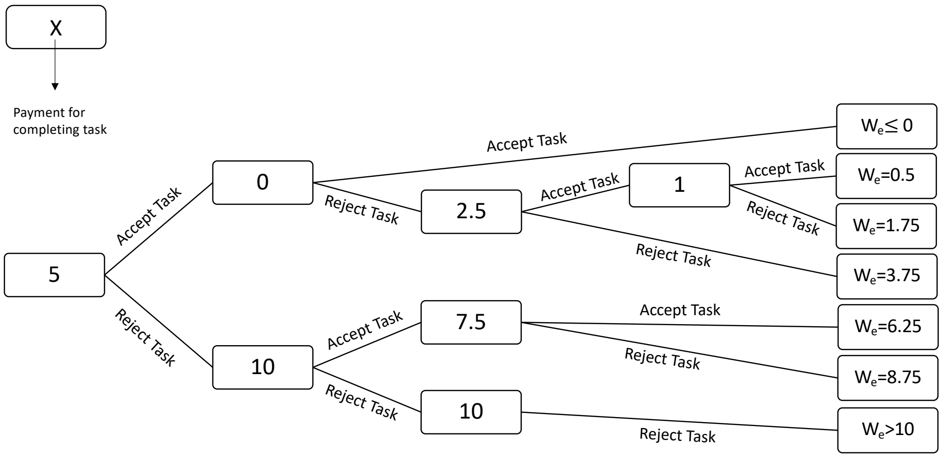
- $74 for halogen bulbs: $22 for bulbs plus $52 for electricity
- $14 for LED bulbs: $2 for bulbs and $12 for electricity

This information is summarized in the figure below:



Notes: Figure shows the information screen displayed to consumers who received information on lifetime operating costs in the experiment.

Figure A4: Staircase to Elicit Willingness to Accept for Effort Task

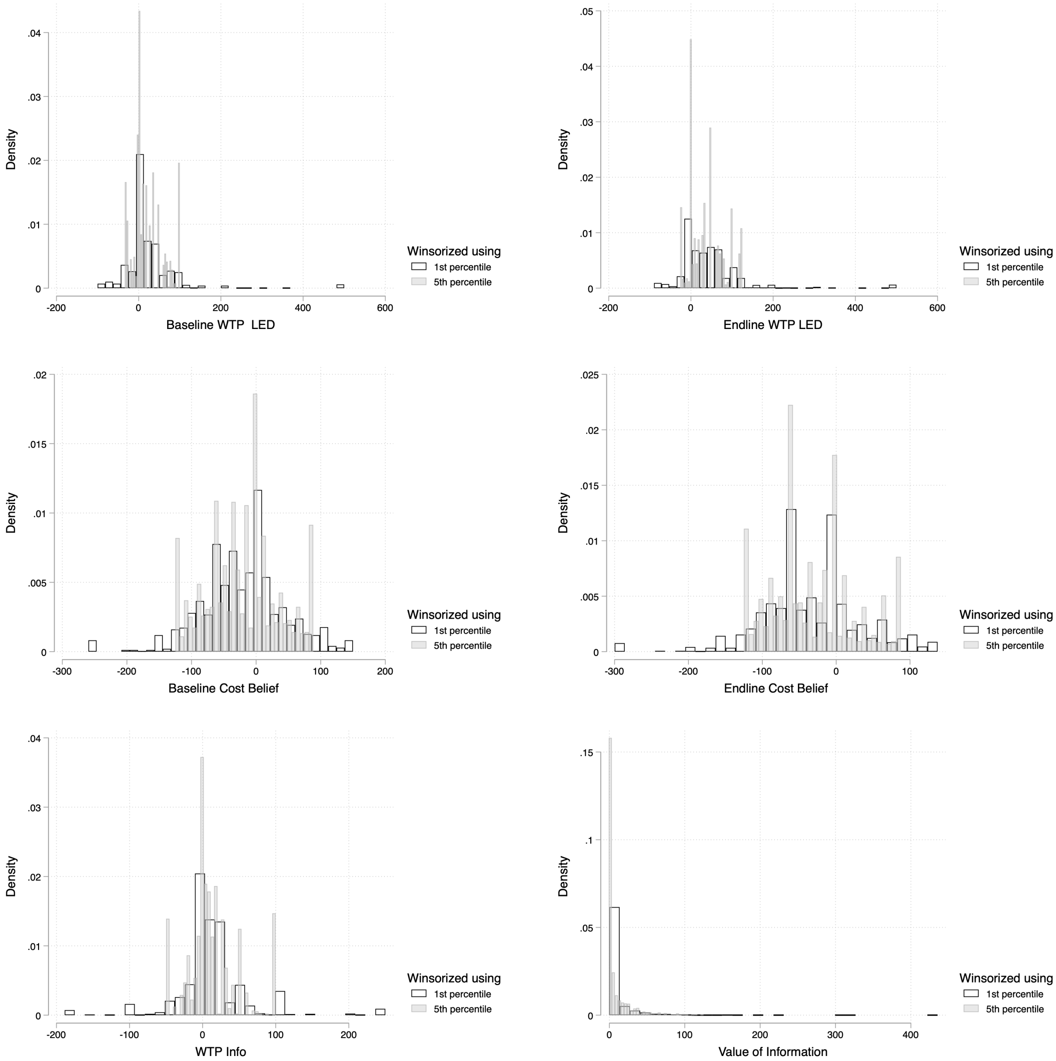


Notes: The staircase procedure works as follows. First, each respondent is asked whether they would like to accept the extra task for an increase in their shopping budget of $5. If they choose the task, they are then asked if they would accept the extra task for no change in their shopping budget. If they had chosen not to accept the extra task, they would be asked whether they would accept it for an increase in their shopping budget of $10. The respondent is then asked the remaining questions depending on their path through the staircase.

B Supplemental: Data and Results

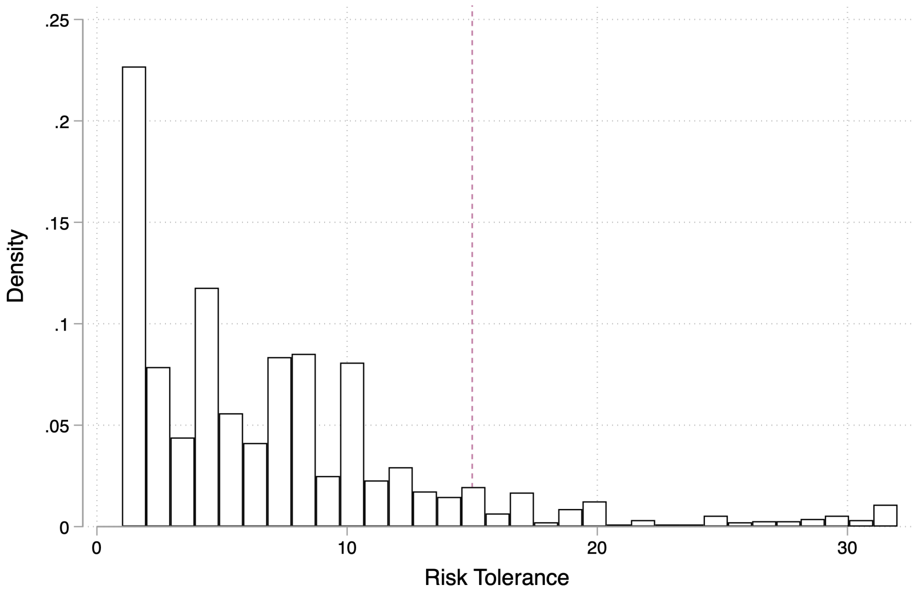
B.1 Descriptive

Figure B1: Winsorizing elicited variables



Notes: WTP LED is willingness to pay for the LED relative to halogen package. Baseline is prior to the information choice. Endline is after the information choice. Cost Beliefs are mean of distribution of beliefs regarding relative total cost of using LED vs halogen light bulbs for ten years of light (negative values indicate cost saving). Information is energy cost and lifetime information of LED and halogen light bulbs.

Figure B2: Distribution of Risk Tolerance



Notes: Distribution of risk tolerance variable from staircase risk preference elicitation task of Falk et al. (2016). Values correspond to implied switching row in staircase task, higher values indicate greater appetite for risk. Individuals with a risk tolerance switching row of above 15 are not risk averse (either risk neutral or risk loving).

Table B1: Experiment Sample: Target and Actual Characteristics

Characteristic	Target	Sample
Household income		
$0-$50K	40%	45.8%
$50-$100K	33%	36.6%
$100K+	27%	17.6%
Gender		
Male	49%	46.2%
Education		
No School/High School Degree/Partial College	62%	54.3%
College Degree	38%	45.7%

Notes: Table shows the targeted and actual distribution of consumer characteristics in the light bulb experiment. Targeted characteristics were chosen to match the characteristics of the United States population.

Table B2: Descriptive Statistics

	mean/sd
Baseline WTP LED	19.48
	(36.22)
Endline WTP LED	38.22
	(42.26)
Baseline Cost Belief	-20.91
	(55.92)
Endline Cost Belief	-31.79
	(57.84)
Baseline Cost Uncertainty	25.91
	(26.96)
Endline Cost Uncertainty	21.21
	(26.22)
WTP Info	12.44
	(34.17)
Received Information (%)	0.75
	(0.43)
WTA Effort	21.63
	(32.25)
Value of Information	8.36
	(17.30)
Pays Electricity Bills (%)	0.94
	(0.25)
Number of People in Home	2.85
	(1.72)
Household Income	67928.50
	(18613.69)
Male	0.46
	(0.50)
Age	47.75
	(16.84)
College Degree (%)	0.46
	(0.50)
Sockets	21.37
	(11.89)
Risk Tolerance	6.97
	(6.41)
Patience	11.34
	(11.18)
Observations	1902

Notes: WTP LED is willingness to pay for the LED relative to halogen package. WTP Info is willingness to pay for information. WTA Effort is williingness to accept to undertake the effort task. Baseline (Endline) is prior to (after) the information choice. Cost Beliefs are mean of distribution of beliefs regarding relative total cost of using LED vs halogen light bulbs for ten years of light (negative values indicate cost saving). Uncertainty is standard deviation of distribution of beliefs. Information is energy cost and lifetime of LED and halogen light bulbs. Patience and Risk Tolerance are elicited using staircase procedure from Falk et al. (2016, 2018).

Table B3: Correlates of WTA in Effort Task

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	WTA for Effort Task							
Value of Information	-0.014							
	(0.046)							
WTP for Information		-0.045**						
		(0.022)						
Received Information (%)			-13.418***					
			(1.691)					
Baseline WTP for LED				0.045**				
				(0.020)				
Baseline Mean Belief About Relative Costs of LED					0.008			
					(0.013)			
Patience Score						-0.306***		
						(0.066)		
Risk Score							-0.184	
							(0.115)	
Time on Information Screen								-0.014**
								(0.006)
Observations	1435	1902	1902	1902	1902	1901	1902	1435

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Table reports correlates of WTA elicited in the Effort Task. Each row presents the results of a separate regression with WTA in the Effort Task as the depedent variable. WTP (WTA) is Willingness to Pay (Willingness to Accept) elicited using a price list or staircase procedure. WTP for LED is WTP relative to halogen. Baseline is prior to the information choice. Cost Belief are stated expectations regarding relative total cost of using LED vs halogen light bulbs for ten years of light (negative values indicate cost saving). Patience and Risk (risk tolerance) are elicited using staircase procedure from Falk et al. (2016, 2018). Time on Information Screen is time spent by respondent viewing information (condition on receiving it).

B.2 Treatment Effects and TESS Experiment Comparison

Tables B4 and B5 report estimated average treatment effects from the Qualtrics light bulb experiment and the TESS light bulb experiment from Allcott and Taubinsky (2015). Table B4 reports results in the Qualtrics sample using an instrumental variables regression where the random price draw is used as an instrument for receiving the information treatment. First stage F statistics are reported at the bottom of the table and demonstrate this instrument is strong. Table B5 reports linear regressions using the TESS sample and random treatment assignment. The dependent variable in Columns (1) and (2) in both tables is Endline WTP. The dependent variable in Columns (3) and (4) is Endline WTP standardized to be mean zero and standard deviation 1. The treatment effects in Columns 3 and 4 can then be read as the effect of treatment in standard deviations. In both experiments information increased willingness to pay for energy efficient light bulbs and these effects are very similar in terms of magnitudes.

Table B4: Treatment Effects Qualtrics Experiment

	(1) Endline WTP	(2) Endline WTP	(3) Std Endline WTP	(4) Std Endline WTP
Information Treatment	23.81***	16.66***	0.563***	0.394***
	(6.982)	(5.691)	(0.165)	(0.135)
Baseline WTP		0.651***		0.0154***
		(0.0235)		(0.000555)
Constant	20.25***	12.97***	-0.425***	-0.597***
	(5.294)	(4.303)	(0.125)	(0.102)
Observations	1902	1902	1902	1902
First stage F	149.6	149.5	149.6	149.5

Standard errors in parentheses

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

Notes: WTP is willingness to pay. Endline is after information treatment. Table reports instrumental variables estimates where the instrument is random information cost drawn in the experiment. Std Endline WTP is standardized to be mean zero and standard deviation one.

Table B5: Treatment Effects TESS Experiment

	(1) Endline WTP	(2) Endline WTP	(3) Std Endline WTP	(4) Std Endline WTP
Information Treatment	2.634***	2.631***	0.357***	0.357***
	(0.418)	(0.234)	(0.0567)	(0.0316)
Baseline WTP		0.796***		0.108***
		(0.0246)		(0.00334)
Constant	2.706***	0.480***	-0.230***	-0.532***
	(0.315)	(0.134)	(0.0427)	(0.0181)
Observations	1203	1203	1203	1203

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

Notes: WTP is willingness to pay. Endline is after information treatment. Std Endline WTP is standardized to be mean zero and standard deviation one.

Tables B6 and B7 report means and standard deviations for treatment groups in the Qualtrics and TESS experiments respectively for the Value of Information as well as Baseline and Endline WTP for energy efficient bulbs. For comparison, subjects in the Qualtrics experiment were asked to compare packages of 12 LED and 24 halogen bulbs. Subjects in the TESS experiment were asked to compare packages of 1 CFL and 2 traditional incandescent bulbs. The Qualtrics experiment was fielded in 2020, the TESS experiment was fielded in 2013. In the Qualtrics experiment, information treatment is random conditional on willingness to pay, so the covariates presented are from a non-random subset of the participants. In the TESS experiment, information treatment is random.

Table B8 reports response durations from the Qualtrics and TESS experiments.

Table B6: WTP for Energy Efficient Bulb and Value of Information: Qualtrics Experiment

	(1)		
	mean	sd	count
Value of Information	8.360	17.298	1435
Baseline WTP	19.595	35.365	1435
Endline WTP	44.207	41.052	1435

Notes: WTP is willingness to pay, std is standard deviation. Baseline is prior to information choice. Endline is after information choice.

Table B7: WTP for Energy Efficient Bulb and Value of Information: TESS Experiment

	(1)		
	mean	sd	count
Value of Information	0.778	1.824	775
Baseline WTP	2.801	7.193	775
Endline WTP	5.340	7.658	775

Notes: WTP is willingness to pay, std is standard deviation. Baseline is prior to information choice. Endline is after information choice.

Table B8: Response Durations

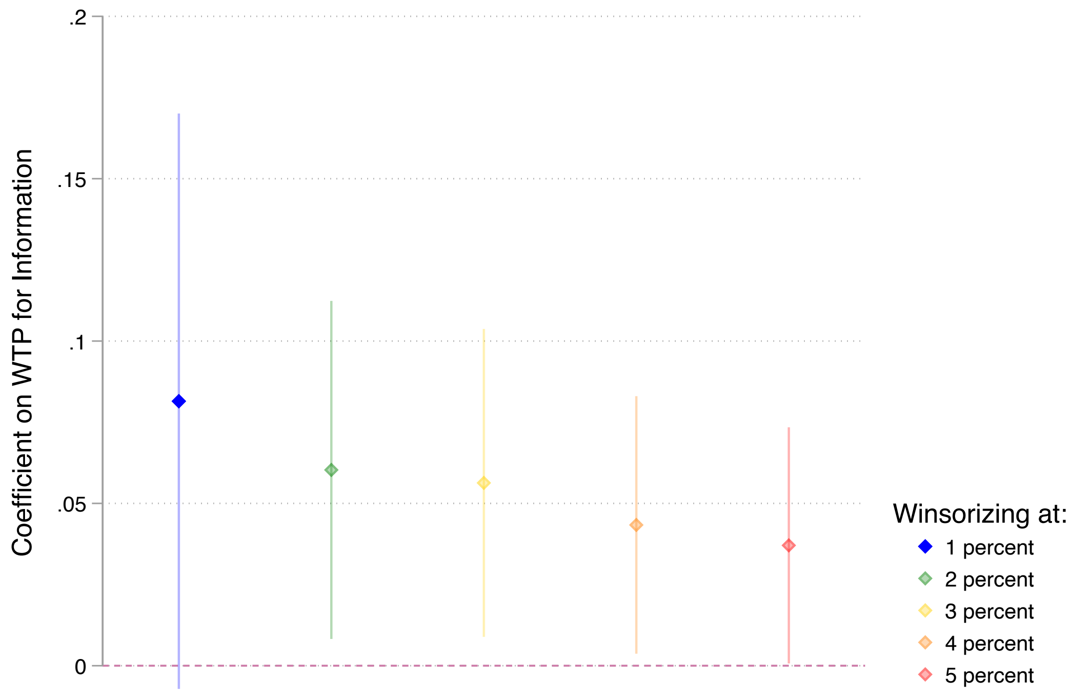
Question	Mean Response Duration	
	Qualtrics	TESS*
Baseline WTP	3 min 45 sec	4 min 18 sec
Endline WTP	1 min 48 sec	2 min 16 sec
Information Screen	2 min	3 min 9 sec

Notes: WTP is willingness to pay, std is standard deviation. Baseline is prior to information choice. Endline is after information choice. Mean durations weighted using sample weights in TESS experiment.

B.3 Treatment of Outliers, Sample Restrictions and Mismeasurement

We first show in Figure B3 that the conclusions are robust to the extent of data winsorization.

Figure B3: Robustness to Winsorizing



Notes: Figure plots estimated coefficient on Willingness to Pay for Information where the dependent variable is Value of Information with different levels of winsorization.

We next use the belief elicitation exercise to exclude individuals who may not understand the tasks or may not be paying close attention. We first exclude consumers who do not report continuous beliefs. For example, a consumer is excluded if they reported some likelihood that the cost difference between the bulbs was in the range \$0-\$25 and some likelihood that the cost difference between the bulbs was in the range \$50 - \$75, but zero likelihood that the cost difference was in the range \$25 - \$50. We exclude the consumer if they reported non continuous beliefs for either the baseline or endline elicitation. Column (1) of Table B9 shows the coefficient on willingness to pay for information is 0.03, and we strongly reject the null hypothesis that it is 1. The next restriction removes consumers with a mean belief that is inconsistent with the question "Do you think the total cost of using LED bulbs would be higher or lower than the total cost of using halogen bulbs?". Again, we exclude a consumer if their response was inconsistent in either the baseline or endline elicitation. The resulting coefficient is reported in column (2) of Table B9. We then exclude consumers with a willingness to pay for the LED bulb above the highest price for the LED in the multiple price list at either baseline or endline. This estimate is reported in column (3) of Table B9.

The next exercise is designed to test the sensitivity of our results to possible mismeasurement in willingness to pay for information which may bias or attenuate the coefficient. In each exercise, we assign a subset of consumers a new willingness to pay for information. We begin by re-coding willingness to pay for information of those who chose information at all prices offered and who therefore have a WTP Info>10. We follow Allcott and Taubinsky (2015) by first assigning these consumers the median of the stated willingness to pay among these consumers. Column (1) of Table B10 shows the coefficient is roughly unchanged from the base specification but the standard error is larger. In Column (2) we re-estimate the regression instead assigning these consumers a willingness to pay for information of 10. This increases the coefficient but we still strongly reject a coefficient of 1 on WTP Info, despite the increased noise associated with the estimate.

We also consider the implications of measurement error due to the price list exercise for those with WTP Info < 10. Rather than assuming that a customer who switches from Information to No Information between prices 7.5 and 10 has WTP Info $= 8.75$, we instead assign them first a WTP Info $= 10$ and then a WTP Info $= 7.5$, and then we assign them a WTP Info $=10$ or WTP Info$=7.5$ with 50% probability. The results of these three exercises are reported in columns (3), (4) and (5) of Table B10. Our conclusions are unchanged.

Table B9: Information Acquisition with Sample Restrictions

	Dependent Variable = Value of Information		
Samples:	Continuous Beliefs	Consistent Beliefs	Marginal WTP for LED
	(1)	(2)	(3)
(a) WTP Info	0.033*	0.033	0.023**
	(0.018)	(0.022)	(0.010)
Observations	1274	911	905
Test optimal acquisition			
F-statistic (a) = 1	2841.84	2010.02	10404.81

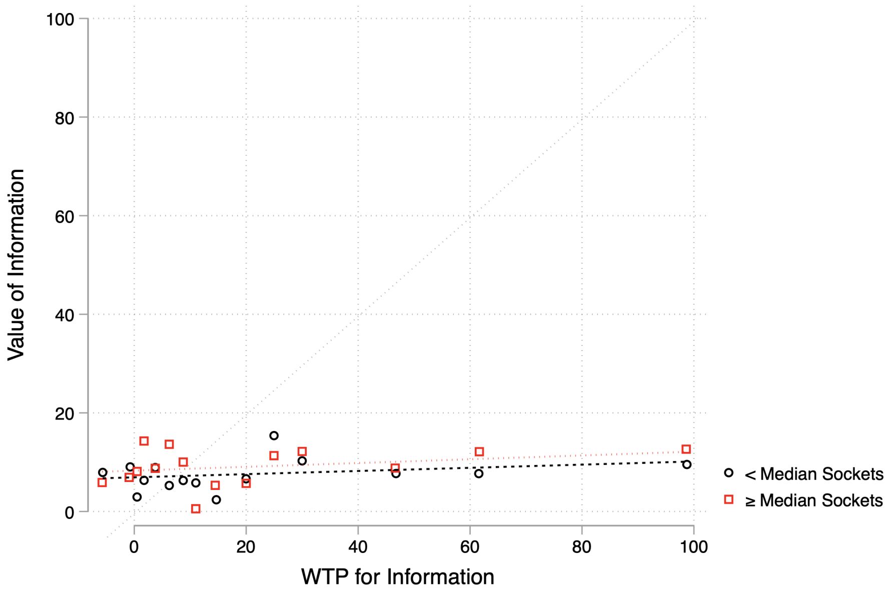
Notes: WTP Info is willingness to pay for information. Column (1) restricts the sample to consumers with continuous beliefs. Column (2) restricts the sample to consumers with a distribution of beliefs consistent with their expectation about which bulb has higher relative costs. Column (3) restricts the sample to consumers with a willingness to pay for the LED bulb package in both elicitations below \$48.75. Observations are weighted using probability weights to account for probability of treatment. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table B10: Information Acquisition with Mismeasurement

	Dependent Variable = Value of Information			
WTP Info Recoding:	Non-marginal WTP		Marginal WTP	
	Median Stated	Max Offered	Stretched	Compressed
	(1)	(2)	(3)	(4)
(a) WTP Info	0.045	0.117	0.013	0.124
	(0.031)	(0.088)	(0.009)	(0.090)
Observations	1435	1435	1435	1435
Test optimal acquisition				
F-statistic (a) = 1	933.49	100.76	11375.27	93.72

Notes: WTP Info is willingness to pay for information. Column (1) consumers with WTP Info $>$ 10 (outside the price list) are assigned a WTP Info equal to the median of stated WTP Info which is 30. Column (2) consumers with WTP Info $>$ 10 (outside the price list) are assigned the highest price of information in the price list which is 10. Column (3) stretches the distribution of WTP Info in the following way: consumers who have a $0 <$ WTP Info < 10 are assigned WTP Info equal to the lowest price at which they chose No Information while consumers who have a WTP Info < 0 are assigned WTP Info equal to the highest price at which they chose Information. Consumers with WTP Info > 10 are assigned the 95th percentile of raw WTP Info. Column (4) compresses the distribution of WTP Info in the following way: consumers who have a $0 <$ WTP Info < 10 are assigned WTP Info equal to the highest price at which they chose Information while consumers who have a WTP Info < 0 are assigned WTP Info equal to the lowest price at which they chose No Information. Consumers with WTP Info > 10 (outside the price list) are assigned the highest price of information in the price list which is 10. Observations are weighted using probability weights to account for probability of treatment. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

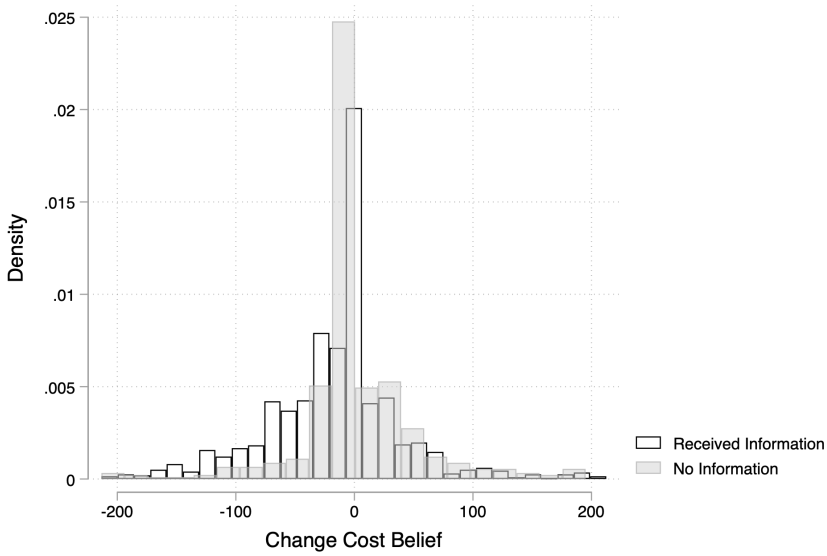
Figure B4: Willingness to Pay for Information and Value of Information by Number of Light Bulb Sockets



Notes: WTP is willingness to pay. Scatter plot of revealed value of information vs binned WTP for information where bins are 20 quantiles of WTP for information in two groups: consumers with below median number of light bulb sockets in their home, and consumers with above median number of light bulb sockets in their home. Median number of sockets is 20, maximum number of sockets is 50.

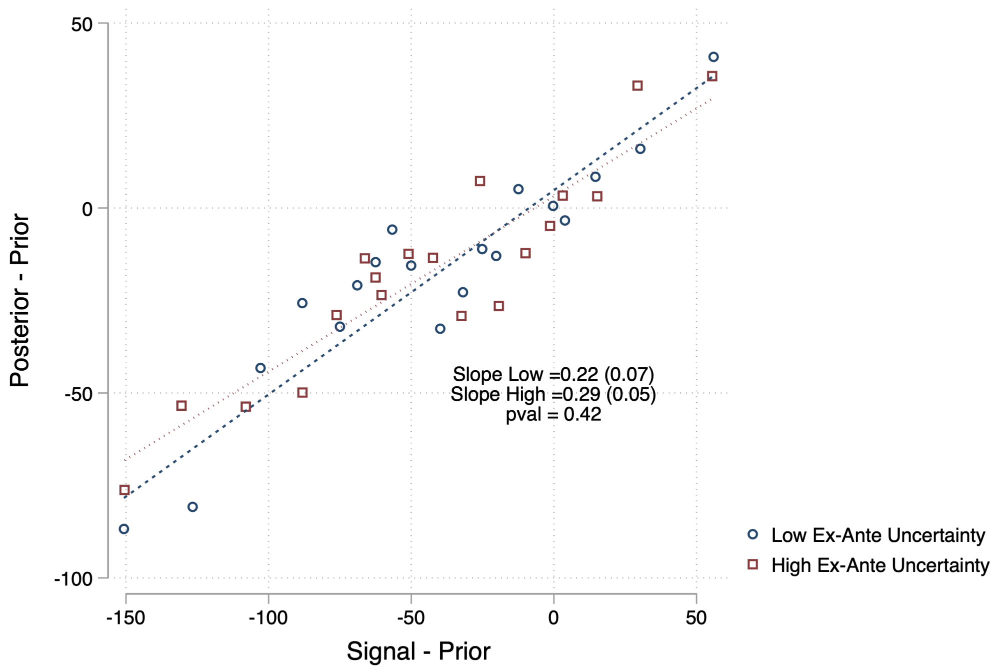
B.4 Beliefs and Learning

Figure B5: Distribution of Difference in Mean Beliefs About Relative Costs of LED Between Baseline and Endline by Information Group



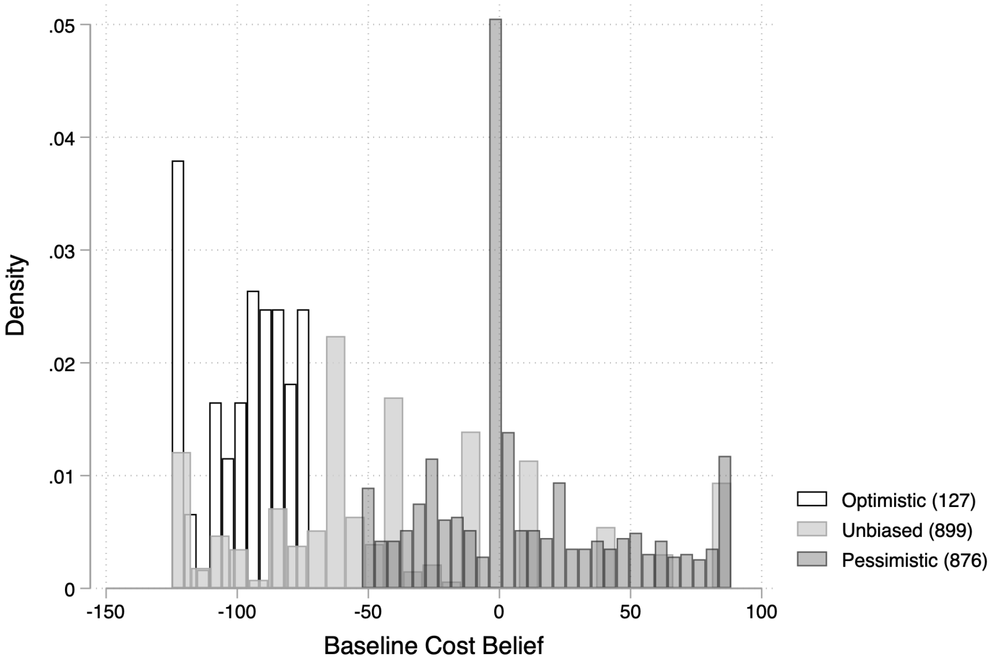
Notes: Difference in mean beliefs ("Posterior" - "Prior") about the total cost of using an LED relative to a halogen incandescent bulb between baseline and endline elicitation by Information Group. Negative values indicate belief that the LED would cost less.

Figure B6: Learning and Prior Uncertainty



Notes: Figure plots the difference between mean endline ("Posterior") and baseline ("Prior") beliefs about the relative cost of LED light bulbs (vertical axis) against the difference between the lifetime cost information provided in the information treatment ("Signal") and baseline beliefs ("Prior") for consumers with above ("High Ex-Ante Uncertainty") and below ("Low Ex-Ante Uncertainty") median baseline uncertainty about the relative costs. Solid line depicts slope for each group. Coefficients and standard errors in parentheses reported in the figure come from estimating the equation in footnote 12 with all components interacted with an indicator for above median level of ex ante uncertainty. Reported p value is for the null hypothesis that the slopes are equal.

Figure B7: Distribution of Mean Baseline Beliefs and Bias



Notes: Histogram shows the distribution of mean baseline beliefs about the total cost of using an LED relative to a halogen incandescent for biased and optimistic, unbiased, and biased and pessimistic consumers. Negative values indicate a belief that the LED would cost less. Bias is evaluated for each consumer based on a test that the mean of the distribution of their beliefs is equal to -$62.50.

Table B11: Learning

	(1)	(2)	(3)
	Dependent Variable = Posterior - Prior		
Received Information × [Signal - Prior]	0.254***		
	(0.037)		
[Signal - Prior]	0.285***		
	(0.034)		
WTP Info	-0.144***		
	(0.035)		
Below Median Time on Information × [Signal - Prior]		0.466***	
		(0.036)	
Above Median Time on Information × [Signal - Prior]		0.584***	
		(0.038)	
Below Median Time on Beliefs × [Signal - Prior]			0.454***
			(0.037)
Above Median Time on Beliefs × [Signal - Prior]			0.582***
			(0.036)
Observations	1902	1435	1435

Standard errors in parentheses

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

Notes: Dependent variable is the difference between mean endline ("Posterior") and baseline ("Prior") beliefs about the difference in costs between the LED light bulbs and incandescent lightbulbs. "Signal" is the lifetime energy cost information provided in the experiment. WTP Info is willingness to pay for information. Signal is the lifetime cost information provided in the information treatment. Time on Information is time spent on the information treatment screen. Time on Beliefs is time spent reporting endline beliefs.

B.5 Supporting Results

Table B12: Alternative Model Specification

	Dependent Variable = Value of Information
	Poisson
	(1)
(a) WTP Info	0.004**
	(0.002)
Observations	1431
(b) Marginal effect	0.03
Test optimal acquisition	
Chi-sq statistic (b) = 1	3877.06

Notes: WTP Info is willingness to pay for information. Table presents coefficient and marginal effect from a Poisson regression. Observations are weighted using probability weights to account for the probability of treatment. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table B13: Determinants of Value of Information

	Dependent Variable = Value of Information			
	(1)	(2)	(3)	(4)
| Baseline WTP LED |	-0.078***	-0.079***	-0.078***	-0.078***
	(0.008)	(0.008)	(0.008)	(0.008)
Baseline Cost Uncertainty	0.003	0.002	0.008	0.016
	(0.020)	(0.020)	(0.022)	(0.023)
WTA Effort		0.002	0.002	-0.001
		(0.016)	(0.016)	(0.016)
Biased + optimistic about LED			-2.136	-1.953
			(1.327)	(1.307)
Biased + pessimistic about LED			-0.563	-0.634
			(1.063)	(1.061)
Patience				-0.038
				(0.042)
Risk Tolerance				-0.231***
				(0.071)
Sockets				0.094**
				(0.040)
Pays Electricity Bills				2.494*
				(1.420)
Observations	1435	1435	1435	1434

Notes: WTA is willingness to accept. Biased = 1 if Mean of Baseline Beliefs About Relative Costs of LED is statistically different to -$62.5 at the 95% level. Baseline is prior to information choice.

Table B14: Actual Welfare with Optimal Subsidies from Nudge in Right Direction

Panel A: Information Subsidy

	Subsidy	Bias	Δ Info(%)	Δ Welfare	Cum Δ Welfare
Low	8.75	20.71	.015	.193	1.073
Medium	8.75	23.994	.015	.241	1.358
High	8.75	27.277	.015	.289	1.643

Panel B: Product Subsidy

	Subsidy	Bias	Δ LED(%)	Δ Welfare	Cum Δ Welfare
Low	12.1875	27.804	.026	.536	.955
Medium	12.1875	32.45	.026	.655	1.158
High	12.1875	37.097	.026	.775	1.361

Notes: This table summarises the welfare impact of optimal subsidies computed when information provision is only a 'nudge in the right direction', true willingness to pay for the LED is not observed by the policy maker and the difference between true willingness to pay and baseline willingness to pay for the LED is 10% (low), 30% (medium), or 50% higher than observed in the experiment.

Table B15: Optimal Subsidies and Welfare with Alternative Estimates of Product Bias

Panel A: Information Subsidy

	Subsidy	Bias	Δ Info(%)	Δ Welfare	Cum Δ Welfare
Low	8.75	20.71	.015	.193	1.088
Medium	8.75	24.02	.015	.242	1.389
High	8.75	27.363	.015	.291	1.703

Panel B: Product Subsidy

	Subsidy	Bias	Δ LED(%)	Δ Welfare	Cum Δ Welfare
Low	12.1875	27.804	.026	.536	.955
Medium	12.1875	32.45	.026	.655	1.158
High	12.1875	37.097	.026	.775	1.361

Notes: This table summarises the welfare impact of optimal subsidies computed assuming actual changes in willingness to pay for the LED as a result of the information intervention were 10% (low), 30% (medium), or 50% higher than observed in the experiment.

C Supplemental: Derivations

C.1 Deriving the Expected Value of Information (Equation (9))

We need an expression for $E\left[\max_j(\nu_{ij} - p_j - \kappa_{ij})\right]$, the first term in equation 3. Define

$$U_i^* = \max_j(\nu_{ij} - p_j - k_{ij} - \epsilon_{ij}), j = \{q, m\}$$
$$= \max_j(\mu_{ij} - \epsilon_{ij})$$

where $-\epsilon_{ij}$ is distributed type 1 extreme value with $E(-\epsilon_{ij}) = -\bar{\epsilon}_j$ and scale parameter σ_i (equivalently $-\epsilon_{ij} \sim G(-(\bar{\epsilon}_j + \frac{\gamma}{\sigma_i}), \sigma_i)$ where γ is Euler's constant i.e. Gumbel distributed). Then by the properties of extreme value type 1 / Gumbel distribution:

$$U^* \sim G\left(\frac{1}{\sigma_i}\ln\left[\exp^{\sigma_i(\mu_{iq}-\bar{\epsilon}_q-\frac{\gamma}{\sigma_i})} + \exp^{\sigma(\mu_{im}-\bar{\epsilon}_m-\frac{\gamma}{\sigma_i})}\right], \sigma_i\right)$$

which can be written:

$$U_i^* = \mu_i^* - \epsilon_i^*$$

where

$$\mu_i^* = \frac{1}{\sigma_i}\ln\left[\exp^{\sigma_i(\mu_{iq}-\bar{\epsilon}_q)} + \exp^{\sigma_i(\mu_{im}-\bar{\epsilon}_m)}\right] \qquad (13)$$

$$-\epsilon_i^* \sim G\left(-\frac{\gamma}{\sigma_i}, \sigma_i\right)$$

combining 13 with the anticipated value of the most preferred product m, re-arranging and noting that:

$$\mu_{im} - \mu_{iq} = (\nu_{im} - p_m - k_{im}) - (\nu_{im} - p_m - k_{im})$$
$$= \widehat{W}_{i,m} - (p_m - p_q)$$

gives 9.

C.2 Deriving the Optimal Information Subsidy

Let $p_L = p_0 - p_1$, i.e. p_L is the relative price of the efficient appliance.

$$\mu(s^I) = Z(s^I) + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq p_L} (W_1 - p_L) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1)$$
$$+ \int_{W^I > p^I - s^I} (\tilde{V} - p^I + s^I) f_{W^I, \tilde{V}}(W^I, \tilde{V}) dW^I d\tilde{V}$$

Now:

$$Z(s^I) = Z - \int_{W^I > p^I - s^I} s^I f_{W^I}(W^I) dW^I$$
$$= Z - \int_{W^I > -s^I} s^I f_{W^I, \tilde{V}}(W^I, \tilde{V}) dW^I d\tilde{V}$$

So:

$$\begin{aligned}
\mu(s^I) &= Z + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq p_L} (W_1 - p_L) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1) \\
&\quad + \int_{W^I > p^I - s^I} (\tilde{V} - p^I) f_{W^I, \tilde{V}}(W^I, \tilde{V}) dW^I d\tilde{V} &(14) \\
&= Z + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq p_L} (W_1 - p_L) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1) \\
&\quad + \int_{W^I > p^I - s^I} (\tilde{V} - p^I) f_{\tilde{V}|W^I}(\tilde{V}|W^I) d\tilde{V} dF_{W^I}(W^I) &(15) \\
&= Z + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq p_L} (W_1 - p_L) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1) \\
&+ \int_{x > p^I - s^I} E_{\tilde{V}|W^I}(\tilde{V} - p^I | W^I = x) \; dF_{W^I}(x) &(16) \\
&= Z + \nu_0 - p_0 - \kappa_0 + \int_{\widehat{W_1} \geq p_L} (W_1 - p_L) f_{\widehat{W_1}, W_1}(\widehat{W_1}, W_1) \\
&\quad - \int_{x > p^I - s^I} E_{\tilde{V}|W^I}(\tilde{V} - p^I | W^I = x) D'_B(x) &(17)
\end{aligned}$$

Where (16) to (17) comes from the $D_B(p^I) = 1 - F_{W^I}(p^I)$ and $D_B(p^I)$ is the market share of the information under biased information acquisition. Then

$$\begin{aligned}
\mu'(s^I) &= -E_{\tilde{V}|W^I}(\tilde{V} - p^I | W^I = p^I - s^I) D'_B(s^I) \\
&= -E_{\tilde{V}|W^I}(\tilde{V} - (W^I + s^I) | W^I = p^I - s^I) D'_B(s^I) \\
&= -E_{\tilde{V}|W^I}(B - s^I | W^I = p^I - s^I) D'_B(s^I) \\
&= E_{\tilde{V}|W^I}(s^I - B | \tilde{V} - B = p^I - s^I) D'_B(s^I) \\
&= (s^I - A(s^I)) D'_B(s^I)
\end{aligned}$$

C.3 Derivation of Welfare Comparison Between Information and Product Subsidies

Base utility, or welfare in the absence of subsidies (μ), can be written:

$$
\begin{aligned}
\mu &= Z + \nu_0 - p_0 - \kappa_0 \\
&+ \int\int\int_{W^I<p^I,\widehat{W}_1\geq p_L} (W_1 - p_L) f_{\widehat{W}_1,W_1,W^I}(\widehat{W}_1, W_1, W^I) dW_1 db\widehat{W}_1 dW^I \\
&\quad + \int\int_{W^I\geq p^I,W_1\geq p_L} (W_1 - p_L - p^I - e) f_{W_1,W^I}(W_1, W^I) dW_1 dW^I \\
&\quad + \int\int_{W^I\geq p^I,W_1<p_L} (-p^I - e) f_{W_1,W^I}(W_1, W^I) dW_1 dW^I
\end{aligned} \tag{18}
$$

where we assume for simplicity that e is fixed across consumers. The first integral captures the utility of consumers who do not acquire information at a price p^I and purchase the efficient product based on uninformed willingness to pay. The second integral captures the utility of consumers who acquire information at price p^I and who purchase the efficient product based on informed willingness to pay. The final integral captures the effort costs of informed consumers who chose the inefficient product.

We can write the welfare with an information subsidy $\mu(s^I)$ as:

$$
\begin{aligned}
\mu(s^I) &= Z + \nu_0 - p_0 - \kappa_0 \\
&+ \int\int\int_{W^I<p^I-s^I,\widehat{W}_1\geq p_L} (W_1 - p_L) f_{\widehat{W}_1,W_1,W^I}(\widehat{W}_1, W_1, W^I) dW_1 d\widehat{W}_1 dW^I \\
&\quad + \int\int_{W^I\geq p^I-s^I,W_1\geq p_L} (W_1 - p_L - p^I - e) f_{W_1,W^I}(W_1, W^I) dW_1 dW^I \\
&\quad + \int\int_{W^I\geq p^I-s^I,W_1<p_L} (-p^I - e) f_{W_1,W^I}(W_1, W^I) dW_1 dW^I
\end{aligned} \tag{19}
$$

The information subsidy changes the bounds of integration - i.e. changes who acquires information and which product they will purchase.

Finally, we can write the welfare from a product subsidy $\mu(s_L)$ as:[30]

$$\begin{aligned}\mu(s_L) &= Z + \nu_0 - p_0 - \kappa_0 &(20)\\ &+ \int\int\int_{W^I<p^I,\widehat{W}_1\geq p_L-s_L} (W_1-p_L) f_{\widehat{W}_1,W_1,W^I}(\widehat{W}_1,W_1,W^I)dW_1 d\widehat{W}_1 dW^I \\ &+ \int\int_{W^I\geq p^I,W_1\geq p_L-s_L} (W_1-p_L-p^I-e) f_{W_1,W^I}(W_1,W^I)dW_1 dW^I \\ &+ \int\int_{W^I\geq p^I,W_1< p_L-s_L} (-p^I-e) f_{W_1,W^I}(W_1,W^I)dW_1 dW^I &(21)\end{aligned}$$

We wish to compute the difference in welfare due to two alternative subsidies, s^I and s_L, i.e. $\Delta\mu = \mu(s^I) - \mu(s_L)$. Table B1 decomposes welfare from changes in light bulb choices into groups of marginal consumers, i.e. consumers who are marginal to the subsidies. Let $K = (W_1 - p_L) f_{\widehat{W}_1,W_1,W^I}(\widehat{W}_1, W_1, W^I)d\widehat{W}_1 dW_1 dW^I$.

Group	Subsidy LED is Marginal To	Conditions	Welfare
A	Both	$A = p_L - s_L \leq \widehat{W}_1 < p_L \leq W_1 \cap p^I - s^I \leq W^I < p^I$	$\int_A K \geq 0$
B	Product	$B = p_L - s_L \leq \widehat{W}_1 \leq W_1 < p_L \cap W^I < p^I - s^I \leq p^I$	$\int_B K < 0$
C	Product	$C = p_L - s_L \leq \widehat{W}_1 < p_L \leq W_1 \cap W^I < p^I - s^I \leq p^I$	$\int_C K \geq 0$
D	Product	$D = p_L - s_L \leq \widehat{W}_1 \leq p_L < W_1 \cap p^I - s^I \leq W^I < p^I$	$\int_D K < 0$
E	Information	$E = \widehat{W}_1 < p_L - s_L \leq p_L \leq W_1 \cap p^I - s^I \leq W^I < p^I$	$\int_E K \geq 0$

Table B1: Decomposing welfare from light bulb purchases by marginal group

Consider first group A in the first row of Table B1. These consumers switch to purchase the LED under both the product and the information subsidy and welfare for this group is identical (and positive) under the two subsidies. Now consider group B in the second row. These consumers remain uninformed under the information subsidy and purchase the incandescent. They switch to purchase the LED under the product subsidy, but their true willingness to pay is less than the social marginal cost of the LED, so their purchase of the LED results in dead weight loss. Group C in the third row also

[30] For completeness, the WTP for information W^I should depend on the relative price of light bulbs p_L and the subsidy s_L as this price difference influences the expected value of information. For parsimony, we suppress this dependence as it does not change the intuition of the welfare differences between the subsidies.

remain uninformed under the product subsidy and switch to purchase the LED under the product subsidy, but their true willingness to pay is greater than the social marginal cost of the LED so welfare from this group is larger under the product subsidy than the information subsidy. Group D in the fourth row become informed under the information subsidy and do not switch to the LED, but under the product subsidy they do switch to the LED, leading to dead weight loss under the product subsidy. Finally group E do not switch to the LED under the product subsidy, but become informed and switch to the LED under the information subsidy, resulting in higher welfare under the information than the product subsidy. Using the groups outlined in Table B1, we can then write the difference in welfare as:

$$\begin{aligned}\Delta\mu &= \int_E K - \left(\int_B K + \int_C K + \int_D K\right) - \int_{p^I - s^I \leq W^I < p^I} (p^I + e) f_{W^I}(W^I) dW^I \\ &= \underbrace{\left(\int_E K - \int_B K - \int_D K\right)}_{\geq 0} - \underbrace{\left(\int_C K + \int_{p^I - s^I \leq W^I < p^I} (p^I + e) f_{W^I}(W^I) dW^I\right)}_{\geq 0}\end{aligned}$$

The first term is the relative advantage of the information subsidy while the second term is the relative advantage of the product subsidy. The preferred subsidy depends on the product distortions due to the product subsidy (the classic Harberger distortions), the remaining bias in information acquisition (after the information subsidy) minus the full cost of information (marginal plus effort cost).