The Welfare Effects of Persuasion and Taxation: Theory and Evidence from the Field

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Abstract

How much information should governments reveal to consumers if consumption choices have uninternalized consequences to society? How does an alternative tax policy compare to information disclosure? We develop a price theoretic model of information design that allows empiricists to identify the welfare effects of any arbitrary information policy. Based on this model, we run a natural field experiment in cooperation with a large European appliance retailer and randomize information regarding the financial benefits of energy-efficient household lighting among more than 640,000 subjects. We find that full information disclosure strongly decreases demand for energy efficiency, while partial information disclosure increases demand. More information reduces social welfare because the increase in consumer surplus is outweighed by the rise in environmental externalities. By randomizing product prices, we identify the optimal tax vector as an alternative policy and show that sizable taxes on energy-inefficient products yield larger welfare gains than any information policy. We also document an important policy interaction: information provision dramatically reduces attention to pecuniary incentives and thereby limits the effectiveness of taxes.

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1 Introduction

Governments frequently provide information to consumers in a variety of markets. Cigarette packages are accompanied by deterrent pictures of black lungs, traffic light systems for groceries assign different colors to food products depending on how healthy they are, and energy efficiency labels assign coarse grades to products depending on the efficiency level. These informational interventions only reveal partial information about the consequences of consumption. For instance, knowing that a refrigerator is certified with an energy efficiency grade informs consumers that it saves costs relative to refrigerators with lower grades but not how the difference in grades translates into absolute monetary savings.

One simple explanation for hiding such potentially relevant information is that it may be difficult to inform consumers with heterogeneous consumption patterns in a concise way. An alternative rationale is that these policies are not just designed to resolve imperfect information but to steer choices toward the social (instead of the private) optimum. While an energy efficiency label may cause consumers to overestimate the monetary savings from energy efficiency and to buy too efficient products from a private perspective, the label may be optimally designed if the reduction in externalities from lower energy consumption (e.g., carbon emissions) outweighs the incremental distortion to consumer surplus from informational frictions. Information design can therefore be seen as a policy tool with which the social planner can internalize externalities.

This paper presents results from a large-scale "natural field experiment" (Harrison and List 2004) in Germany conducted with over 640,000 subjects to quantify the welfare effects of information design. On the basis of a theoretical model, we develop an experimental design that identifies the effects of coarse information on consumer surplus, firm profits, and externalities. We partner with one of Europe's largest retailers for household lighting and randomize signals with different degrees of informativeness regarding the monetary savings of energy efficiency. We additionally randomize product prices to identify own-price and cross-price demand elasticities under these various informational interventions and identify the optimal tax vector both as a complementary and an alternative policy to information provision.

The theoretical model developed in this study creates a bridge between information theoretic models and applied welfare analysis. Our price theoretic approach offers a coherent framework to empirically evaluate any arbitrary information policy. The model also creates a direct connection between information economics and the taxation literature by allowing for an apples-to-apples comparison between the efficiency consequences of informational policies, tax policies, and a policy mix that uses both information and taxation.

The model guides the design of a natural field experiment in the market for energy-using durables. Our cooperation with the household lighting retailer is motivated by an extensive literature on the "energy efficiency gap" (Jaffe and Stavins 1994), hypothesizing that households underinvest in energy efficiency because they underestimate the associated savings. Residential lighting accounts for around 20 percent of final electricity consumption in European households and has one of the highest savings potentials among appliances (De Almeida et al. 2011). Governments have also substantially regulated the lighting market in a variety of ways. Besides the mandatory energy efficiency labels, less energy-efficient light bulbs get banned in many countries around the world, such as Argentina, Australia, Canada, China, the European Union, and Russia to name only a few examples. While the United States initiated a phaseout in 2012, many of the regulations have been reversed recently by the Trump administration (New York Times 2019).

In the field experiment we randomize banners in the online store that inform consumers about the energy savings of efficient lighting technologies. We vary the informativeness by showing some subjects how much efficient lighting saves in percentage, while showing others how much it saves in percentage *and* how these relative savings translate into *absolute* monetary savings. This systematic variation of informativeness allows us to observe whether hiding potentially relevant information (absolute savings) boosts demand for energy efficiency beyond the privately optimal level. Under the assumption that choices under the more informative signal identify choices under full information, we can evaluate a) the informational distortions that are currently present in the market and b) how these frictions change with the disclosure of partially informative signals. Using detailed data on firm profits provided by the retailer and estimates on the social cost of electricity consumption, we identify which information design has the largest positive effect on overall welfare. In addition, random price variation in each informational group identifies how corrective taxes can substitute or complement these informational interventions.

Our results suggest that—different from priors formed on the basis of previous findings—the average consumer *overestimates* savings from purchasing energy-efficient LED bulbs. Specifically, telling subjects that an LED bulb saves 90 percent in energy costs relative to an incandescent increases demand for energy efficiency. However, informing subjects that this 90 percent translates into an average annual savings of approximately 11 euros substantially decreases demand for LEDs and increases demand for alternative (less efficient) technologies. Furthermore, both informational interventions dramatically decrease attention to price discounts, suggesting that information provision lowers the effectiveness of taxes. A second experiment in the same store elicits savings beliefs and provides evidence that the underlying channel of the observed demand responses is a change in beliefs. We find that subjects in the control group substantially overestimate savings from LEDs, and showing subjects the savings only in percentage increases the degree of overestimation even further. By contrast, providing subjects with information on both the relative and absolute monetary savings strongly reduces the extent of this overestimation. These movements in beliefs are in line with the point estimates of demand responses from the first experiment. They are also robust to the inclusion of heterogeneity in electricity prices and utilization behavior.

Structural estimates suggest that consumers overvalue LEDs by about 0.56 euros per bulb and undervalue less efficient alternatives by 0.67 euros per bulb. Importantly, the more informative signal decreases welfare relative to no information provision because the sum of the increase in consumer surplus from more informed choices and the rise in firm profits is outweighed by the increase in environmental externalities. Overall, less information is socially more efficient: while the less informative signal dominates the more informative one, no information disclosure dominates both informational interventions. The optimal tax policy as an alternative policy dominates both information designs and is characterized by a large tax of 2.26 euros per bulb on energy-inefficient technologies and a subsidy of 1.54 euros on LEDs. Taxes and subsidies need to be substantially larger than this when combined with one of the informational interventions since information reduces attention to financial incentives.

Our study contributes to four strands of literature. First, it translates detailed information theoretic models to a price theoretic model that imposes little structure and is useful for applied welfare analysis of informational policies. Our model combines the concept of "informativeness" (Blackwell 1951) with the sufficient statistics approach for welfare analysis in public finance (Chetty 2009). Our approach may be broadly used to evaluate the efficiency consequences of persuasive communication, in which a sender decides on how much information to reveal to a receiver. This includes information theoretic games, such as verifiable message (Milgrom 1981) and Bayesian persuasion (Kamenica and Gentzkow 2011), but is not restricted to these particular settings. Since our framework makes no assumption of how consumers update beliefs or on the accuracy of their priors, it also captures models in which the receiver's belief formation is distorted due to some of the documented behavioral biases (e.g., Falk and Zimmermann 2018, Enke and Zimmermann 2019, Zimmermann 2020). Most of the existing empirical studies on persuasive communication document only reduced-form effects of persuasion (for an overview, see DellaVigna and Gentzkow 2010).[1] We still lack an understanding of how persuasion affects social welfare, despite the fact that cost-benefit analyses are crucial for policy making. For this purpose, we derive a set of empirically identifiable sufficient statistics to evaluate the efficiency effects of persuasion and provide the first empirical evidence from a natural field experiment.

Second, we add to a small body of the recent literature in public finance that analyzes how the distortions created by informational frictions and behavioral biases can be countered

[1] Coffman, Featherstone, and Kessler (2015) develop a model based on Bayesian agents that aims to explain why information disclosure affects behavior in some of these studies, while leaving it unaffected in others.

by classical fiscal tools such as taxes and subsidies.[2] These "internality taxes" or "sin taxes" follow a simple rationale: if consumers do not make fully informed choices, the social planer may change relative prices through taxes such that uninformed consumers make quasi-informed choices. The idea to use taxes to correct behavioral frictions goes back to O'Donoghue and Rabin (2006), who study the optimal tax to correct present-biased consumption choices. Recent studies have analyzed the optimal subsidy for energy-efficient light bulbs (Allcott and Taubinsky 2015) and optimal energy taxes (Allcott, Mullainathan, and Taubinsky 2014) when consumers underestimate the benefits of energy efficiency, as well as the optimal sugar tax when consumers do not fully take into account the associated negative health consequences (Allcott, Lockwood, and Taubinsky 2019). An unanswered, but intuitive, question in this context is how information design would compare to these taxes and affect welfare. Our paper allows for such a comparison by systematically varying the informativeness of a signal and by comparing this variation to a variation in the size of a tax. Our theoretical approach can be considered as part of Bernheim and Rangel (2009)'s framework of behavioral welfare analysis that provides guidance to evaluate efficiency effects when observed behavior differs from revealed preferences. Mullainathan, Schwartzstein, and Congdon (2012) and Farhi and Gabaix (2020) develop general frameworks to integrate behaviorally motivated taxes and alternative nonprice interventions ("nudges") into public finance. Our model fits into these frameworks in that we study the welfare effects of "information nudges" when consumers are imperfectly informed about the consequences of consumption.

Third, we add to the emerging literature in structural behavioral economics (DellaVigna 2018) that identifies structural parameters proposed in theories at the intersection of psychology and economics. Related studies have analyzed inattention to shrouded costs of health insurance plans (Handel and Kolstad 2015), sales taxes (Chetty, Looney, and Kroft 2009, Taubinsky and Rees-Jones 2017), and right digits of prices (Lacetera, Pope, and Sydnor 2012). To the best of our knowledge, our study joins only two existing studies that have taken this structural approach to a natural field experiment: DellaVigna, List, and Malmendier (2012) who study altruism and disutility from social pressure and DellaVigna et al. (2016) who study the social recognition utility from voting.

Fourth, an extensive literature in energy economics raises the question whether households underinvest in energy efficiency, in part because they underestimate the associated savings. Empirical research motivated by this idea generally finds mixed results. A study by Larrick and Soll (2008) shows that consumers perceive the nonlinear relation between the miles-per-gallon of a vehicle and its gas consumption to be linear. A survey by Attari et al. (2010) finds that households misperceive the energy savings of various conservation activities

[2] Bernheim and Taubinsky (2018) provide a comprehensive overview of the exisiting literature.

and appliance replacements. Allcott and Wozny (2014) analyze transaction data of vehicle purchases and show that demand responds less to a change in a vehicle's discounted fuel costs than to its purchase price. Newell and Siikamäki (2014) provide evidence from a stated choice experiment that information about energy efficiency increases investments in energy-efficient water heaters. Houde (2017) studies observational data of refrigerator sales and finds that the US energy efficiency label increases demand for energy efficiency. A recent field study in Italy by d'Adda, Gao, and Tavoni (2020) finds that displaying energy costs decreases demand for energy-efficient refrigerators. Allcott and Taubinsky (2015) show that information about the savings of energy-efficient compact fluorescent light (CFL) bulbs increases willingness-to-pay for CFLs in a survey experiment but has no effect on demand in a field experiment. Another field trial by Allcott and Knittel (2019) randomizes information about the benefits of a car's fuel economy among vehicle shoppers, and their results show a precisely estimated null effect of information on investments in fuel economy.

Our results cast further doubt on the hypothesis that consumers underinvest in energy efficiency by showing that the average customer of one of Europe's largest retailers for household lighting *overvalues* the monetary savings of energy-efficient light bulbs. We also provide an auxiliary analysis of historical transaction data showing that purchasing patterns have become substantially more energy efficient over recent years, making the prevalence of an energy efficiency gap in the market for household lighting unlikely.

The rest of the paper proceeds as follows. Section 2 introduces the theoretical framework. The experimental design is discussed in Section 3. We document the reduced-form results in Section 4 and present structural estimates in Section 5. In Section 6, we discuss how well our results resonate with related previous findings in the literature. Section 7 concludes.

2 Theoretical Framework

We start by introducing our theoretical framework, which provides the basis for the experiment's design and the subsequent empirical estimations. Our main goal is to develop a model that captures consumer behavior under imperfect information and can be used to empirically identify the relevant behavioral parameters for applied welfare analysis. This requires a general formulation that allows for any arbitrary consumption bundle and substitution patterns. We begin with a representative agent framework and then introduce heterogeneity.

2.1 The Consumer's Choice under Imperfect Information

A consumer gets deterministic utility $v(\mathbf{x})$ from consumption vector $\mathbf{x} = (x_1, x_2, ..., x_J)$ and faces pre-tax market prices $\mathbf{p} = (p_1, p_2, ..., p_J)$ and per unit taxes $\mathbf{t} = (t_1, t_2, ..., t_J)$. We make the standard assumptions regarding the properties of v: we assume that $\frac{\partial v}{\partial x_j} > 0$ and $v()$

is strictly concave. The consumer also receives state-dependent utility $\omega'\mathbf{x}$ from the vector of states $\omega = (\omega_1, \omega_2, ..., \omega_J)$ where every ω_j is drawn by nature from the distribution F_j before consumption choices are made. Each product may therefore include an uncertain component that affects consumer utility. While ω may be truly stochastic, this formulation also allows for deterministic state vectors that are unknown to the consumer. For instance, ω_j may represent the energy costs of product j that are a deterministic function of energy consumption and energy prices. If consumers have no uncertainty over their consumption, then ω_j is deterministic but may still be uncertain from the consumer's perspective.

We assume that utility is quasi-linear and let N denote the numeraire good that is sold at a price of unity. The consumer's budget, $Y(\mathbf{t}) = Z + T(\mathbf{t})$, is the sum of income, Z, and government transfers, $T(\mathbf{t})$. Tax revenue is recycled in lump-sum payments to consumers such that any tax policy leaves net income unchanged. Preferences are described by

$$u = v(\mathbf{x}) + Y(\mathbf{t}) + (\omega - \mathbf{p} - \mathbf{t})'\mathbf{x}. \tag{1}$$

The consumer expects the states of the world to be $\hat{\omega}(\mathbf{s}) = (\hat{\omega_1}(s_1), \hat{\omega}_2(s_2), ..., \hat{\omega_J}(s_J))$, where each expectation about product j is a function of an information parameter s_j. We assume that $\hat{\omega}_j$ is differentiable in s_j, and we refer to the vector $\mathbf{s} = (s_1, s_2, ..., s_J)$ as a *signal*. Note that our use of the word signal deviates from the one in information economics, where a signal typically refers to an information structure rather than to a parameter vector.[3] Without loss of generality, we define $\mathbf{s}$ such that $\mathbf{s} = \mathbf{0}$ is a completely uninformative signal.

Let $\mathbf{b}(\omega, \mathbf{s}) = \omega - \hat{\omega}(\mathbf{s})$ be the deviation of the realized state from the state expected by the consumer. Every entry in $\mathbf{b}$ is denoted by $b_j(\omega_j, s_j) = \omega_j - \hat{\omega}_j(s_j)$. Note that if $b_j > 0$, the consumer undervalues good j while overvaluing good j when $b_j < 0$. We will say that a consumer *misperceives* the realized benefits (or costs) of product j whenever $b_j \neq 0$. If expectation and realization are equal for all products, there are no informational frictions in the current state and $\mathbf{b}(\omega, \mathbf{s}) = \mathbf{0}$. Models of rational expectations are a special case in our model in which the assumption is made that $\mathbb{E}[\mathbf{b}] = \mathbf{0}$ (i.e., there is no informational bias in expectation). Our model imposes no structure on the consumer's belief formation. Consumers can have a correct prior and use Bayes's rule to update beliefs. They may also have biased beliefs, which in our model corresponds to $\mathbb{E}[\mathbf{b}] \neq \mathbf{0}$, and/or may update information incorrectly due to some of the documented biases in belief formation (Falk and Zimmermann 2018, Enke and Zimmermann 2019, Zimmermann 2020).

We further allow for a particular interaction between signals and taxes, namely that

[3] More formally, a signal is typically defined as a pair (π, R) that maps a state of the world, $\phi \in \Phi$, into a distribution over signal realizations: $\pi : \Phi \mapsto \Delta(R)$. Here, $\Delta(R)$ is the set of all probability distributions on the set of signals R. An information policy is thus characterized by a set of conditional likelihoods $\pi(r|\phi)$ and the marginal distribution $\Delta(\phi)$.

signals may crowd out (or crowd in) cognitive attention to pecuniary incentives. For instance, the provision of potentially complex information may reduce cognitive resources to engage with financial incentives. We denote the tax salience parameter by $\theta(\mathbf{s})$ in the spirit of Chetty, Looney, and Kroft (2009). If $\theta \in [0,1)$, the consumer's demand reacts less to a change in the tax rate than to a change in price. If $\theta > 1$, the consumer overreacts to taxes. We let θ be a function of the signal and assume that it is differentiable in $\mathbf{s}$. We also refer to θ as "attention to pecuniary incentives" more generally, as in our experiment we introduce a "subsidy" by providing consumers with salient price discounts. For this reason, we also make the specific assumption that $\theta(\mathbf{0}) = 0$ such that consumers are fully attentive to pecuniary incentives when no information is provided. This assumption is reasonable in our empirical setting where the financial incentive comes in the form of a salient discount on particular products, but this may be less realistic in other scenarios. While our analysis may be easily extended to cases where $\theta(\mathbf{0}) \neq 0$, we maintain this assumption to ease notation and for clarity.

We can now write demand, denoted $\mathbf{x}(\mathbf{p}, \mathbf{t}, \mathbf{s})$, as

$$\mathbf{x}(\mathbf{p}, \mathbf{t}, \mathbf{s}) = \arg\max_{\mathbf{x}} \left\{ v(\mathbf{x}) + Y(\mathbf{t}) + (\omega - \mathbf{b}(\omega, s) - \mathbf{p} - \theta(\mathbf{s})\mathbf{t})'\mathbf{x} \right\}. \tag{2}$$

Throughout the following derivations, we assume that demand functions are locally linear in prices such that $\frac{\partial^2 x_j}{\partial p_j^2} \approx 0$ for all j, and $\frac{\partial^2 x_j}{\partial p_k^2} \approx 0$ for all pairs (j,k).

In the definition of DellaVigna and Gentzkow (2010) our model is "belief based," as information provision affects receivers' utility only through a change in beliefs. An alternative formulation is a "preference-based" model in which a signal realization directly affects receiver beliefs (e.g., when consumers experience direct utility from advertisement as in Becker and Murphy (1993)). Our model of information disclosure therefore focuses on the idea in persuasion games that the sender can change the receiver's behavior by changing information instead of changing incentives.

2.2 The Social Planner's Choice

The social planner chooses a signal $\mathbf{s} = (s_1, s_2, ..., s_J)$ and observes the realized state of the world ω. We do not need to make any assumption on whether the social planner can commit to the choice of a signal before the state realizes.[4] The reason we do not require an assumption regarding the commitment ability of the social planer is that we refrain from specifying how the consumer updates beliefs and strategically interacts with the social planner. Instead we analyze how a given demand response to a signal affects economic efficiency. We therefore

[4]For instance, in persuasion games with verifiable messages (Milgrom 1981) the sender observes the state and then chooses to send a report to the receiver. In this case, the information structure chosen by the policymaker can be viewed as a reporting strategy. In Bayesian persuasion games (Kamenica and Gentzkow 2011) the sender first chooses and, importantly, commits to an information structure before the state realizes.

lose much of the rich insights that information theoretic models produce. In return we get empirically estimable sufficient statistics to evaluate the welfare effects of any arbitrary information policy independent of the particular game theoretic framework.

The social planner's objective function, conditional on a state of the world, is the social welfare function, which we define as the indirect utility function, plus producer surplus, minus any externalities. We denote the marginal externalities by $\epsilon = (\epsilon_1, \epsilon_2, ..., \epsilon_J)$ and the marginal firm markups by $\mathbf{m} = (m_1, m_2, ..., m_J)$. We assume that marginal markups and marginal externalities are constant and exogenous to the policies we analyze. The social welfare function conditional on a state of the world is therefore

$$W = u(\mathbf{x}(\mathbf{p}, \mathbf{t}, \mathbf{s}), \mathbf{p}, \mathbf{t}, \omega) + (m - \epsilon)'\mathbf{x}(\mathbf{p}, \mathbf{t}, \mathbf{s}). \tag{3}$$

For simplicity, we will analyze welfare effects *conditional* on a realized state. This is practical for many empirical applications in which the empiricist wants to evaluate an information policy after a state has realized. Similarly, conditioning on a state is useful for many situations in which the state is truly deterministic but is unknown to the consumer. Note, however, that our analysis is easily extended to an ex-ante welfare evaluation just by taking the expectation of the right-hand side of equation 3 over the distribution of the states.

The social planner can now choose information and taxation to maximize welfare by choosing the policy vector $\rho = (\mathbf{t}', \mathbf{s}')$. Before we analyze the effect of such policies on welfare, we first define a way to rank signals in terms of how much they reduce informational frictions.

Definition 1. *We call* $\mathbf{s} = (s_1, s_2, ..., s_J)$ *more informative than* $\mathbf{s}' = (s'_1, s'_2, ..., s'_J)$ *iff* $\mathbb{E}_{F_j}[b_j(\omega_j, s_j)] \leq \mathbb{E}_{F_j}[b_j(\omega_j, s'_j))]$ *for all* j.[5]

We therefore call a signal more informative than an alternative signal if it induces choices that reduce informational frictions in expectation more than the alternative signal. If consumers have correct priors and use Bayes's rule to update beliefs, then this definition coincides with the Blackwell order of informativeness (Blackwell 1951). Since we are not restricted to Bayesian agents, our definition of informativeness also captures situations in which consumers make systematic mistakes due to some behavioral bias but in which the information policy reduces these mistakes. We call an information policy that perfectly reveals the state of the world *fully informative.*

Definition 2. *We call* $\mathbf{s} = (s_1, s_2, ..., s_J)$ *fully informative iff* $s_j = s^*_j$ *with* $b_j(\omega_j, s^*_j) = 0$ *for all* j.

In the following section we show how the effect of information provision on beliefs can be empirically identified through estimable reduced-form demand elasticities.

[5] The index of the expectation operator indicates the distribution over which the expectation is taken.

2.3 Identifying Informational Frictions

We aim to recover the effect of signal $\mathbf{s}$ on misperceptions in beliefs $\mathbf{b}(\mathbf{s})$ without imposing any structure on belief formation. The challenge in a setting with multiple goods is that a signal may cause the consumer to update beliefs about multiple products simultaneously. For instance, information regarding the health risks of beer consumption may affect a consumer's belief about the risks associated with other alcoholic beverages or even about complementary goods like potato chips. Therefore, the observed change in demand for any one good may be caused by changes in beliefs about that good but may also be caused by changes in beliefs about multiple substitutes and complements.

As Lemma 1 shows, this simultaneous change in multiple belief distributions implies that to identify the changes in beliefs induced by a signal, one needs to know all own-price and cross-price demand elasticities. The reason is that the changes in beliefs act like changes in the goods' prices. Therefore, changes in demand will, to a first-order approximation, be given by the matrix of cross-price effects times the change in misperceptions. For an observed change in behavior induced by a signal, this relation can be inverted to infer the changes in misperceptions. To establish this formally, we first introduce some additional notation. Let the vector of demand responses to an information policy be $\Delta\mathbf{x} = (\Delta x_1, \Delta x_2, ..., \Delta x_J)$, where $\Delta x_j = \int_{\mathbf{z}=\mathbf{s}}^{\mathbf{z}=\mathbf{s}+\boldsymbol{\Delta}\mathbf{s}} \frac{dx_j(\mathbf{p},\mathbf{t},\mathbf{s},\omega)}{d\mathbf{s}} d\mathbf{z}$ is the demand response of product j to a change in the information policy from $\mathbf{s}$ to $\mathbf{s} + \boldsymbol{\Delta}\mathbf{s}$. Furthermore, let $\Delta\mathbf{x}^*$ be the demand response to a fully informative signal, $\mathbf{s}^*$, such that $\mathbf{b}(\mathbf{s}^*, \omega) = \mathbf{0}$. The empirical analog to $\Delta\mathbf{x}$ is the vector of treatment effects to an information policy. For example, $\Delta\mathbf{x}$ can be the demand response to an energy efficiency label on energy-using durables, a health label on food products, or a fair-trade label on textile products. This policy may only partially eliminate consumers' misperceptions, further exacerbate them, or perfectly inform consumers. In the latter case, $\boldsymbol{\Delta}\mathbf{x} = \boldsymbol{\Delta}\mathbf{x}^*$.

Furthermore, denote $\mathbf{E} = (\frac{dx_j}{dp_k}) \in \mathbb{R}^{I\times K}$ as the Slutksy matrix whose elements are the own-price and cross-price derivatives of demand. Lemma 1 formalizes the link between $\Delta\mathbf{x}$, $\Delta\mathbf{x}^*$, and E and the changes in beliefs.

Lemma 1. *Consider an information policy* $\mathbf{s}$ *that changes the misperception vector from* $\mathbf{b}$ *to* $\mathbf{b} + \Delta\mathbf{b}$*. We can approximate the change of the misperceptions about* ω *by*

$$\Delta\mathbf{b} \approx E^{-1}\Delta\mathbf{x}. \tag{4}$$

Similarly, we can approximate the pre-intervention vector of misperceptions by

$$\mathbf{b} \approx -E^{-1}\Delta\mathbf{x}^*. \tag{5}$$

Lemma 1 establishes that we can approximate the change in consumers' misperceptions through knowledge of the Slutsky matrix and the demand response to the associated information policy. If the information policy is fully informative, we have $\mathbf{\Delta b} = -\mathbf{b}$ and can recover the misperceptions in beliefs that prevailed in the market before the information policy was implemented. When deriving welfare effects in the next section, we make the assumption that the approximations in Lemma 1 are exact (i.e., hold with equality). This assumption simplifies derivations and is less restrictive for smaller policy changes.[6]

2.4 Welfare Effects of Information and Taxation

Having established the relation between demand responses and beliefs, we can now express the welfare effect of different policy interventions in empirically observable quantities. The social planner may decide between an information policy, a tax policy, and a policy mix that uses both information and taxation. We directly start by analyzing the welfare effect of a policy mix because each policy tool in isolation can be viewed as a special case of a policy mix. Proposition 1 characterizes the welfare effect of a policy mix in a previously unregulated market, by which we mean $\rho = (\mathbf{0}', \mathbf{0}^{'})$.

Proposition 1. *The welfare effect of a policy mix that changes the policy vector from* $\rho = (\mathbf{0}', \mathbf{0}')$ *to* $\rho + \mathbf{\Delta}\rho = (\mathbf{\Delta t}', \mathbf{\Delta s}')$ *is given by*

$$W(\mathbf{\Delta t}, \mathbf{\Delta s}) - W(\mathbf{0}, \mathbf{0}) \approx \underbrace{(\Delta\mathbf{t}'E + \Delta\mathbf{x}')}_{\textit{Demand response to policy}} \left(\underbrace{\frac{1}{2}\Delta\mathbf{t} + E^{-1}(\frac{1}{2}\Delta\mathbf{x} - \Delta\mathbf{x}^*)}_{\textit{Effect on consumer surplus}} + \underbrace{(\mathbf{m} - \epsilon)}_{\textit{Effect on social frictions}} \right). \tag{6}$$

Denote an optimal tax vector in a policy mix by $\mathbf{t}^*_{\mathbf{m}}$. *Then an optimal tax vector is given by*

$$\mathbf{t}^*_m = \left(E^{-1}\mathbf{\Delta x}^*(\mathbf{s}) - \mathbf{m} + \epsilon\right)\theta(\mathbf{s})^{-1}. \tag{7}$$

Proposition 1 provides an intuitive demonstration of the efficiency effects of a policy intervention. Equation 6 consists of three parts. The first term is the effect on demand due to a change in the tax rate and in the information policy. The second term is the per unit change in consumer surplus due to the policy. The first part of the second term, $\frac{1}{2}\mathbf{\Delta t}$, is just the "Harberger triangle" to consumer surplus in a previously untaxed market (Harberger 1964). The second part, $E^{-1}(\frac{1}{2}\mathbf{\Delta x} - \mathbf{\Delta x}^*)$, is the change in distortions from changing informational

[6] Together with the assumption that demand derivatives with respect to price are locally linear, these assumptions imply that misperceptions are locally linear in the respective information parameter (i.e., that $\frac{\partial^2 b_i(s_i)}{\partial s_i^2} \approx 0$ for all i).

frictions.

The third part of equation 6 provides the marginal effect of the policy on social frictions (i.e., firm markups and externalities). The social planner needs to weigh the effect of the policy on consumer surplus with the effect on these social distortions.

The optimal tax vector is set such that it corrects any market frictions that remain after the signal has changed consumers' beliefs. Importantly, $\mathbf{\Delta x}^*(\mathbf{s})$ is the optimal demand response to a fully informative signal *after* the information policy has been implemented. If the information policy was fully informative, then $\mathbf{\Delta x}^*(\mathbf{s}) = \mathbf{0}$ and the optimal tax just needs to internalize markups and externalities. However, it may also be that the signal only partially reduced informational frictions such that the social planner needs to take into account any remaining misperceptions when setting taxes. Also note that taxes need to be larger (smaller) when information decreased (increased) attention to pecuniary incentives (i.e., when $\theta(\mathbf{s}) \neq 1$) since every market friction is scaled by the inattention parameter. The optimal tax simplifies to the standard Pigou tax when markets are perfectly competitive ($\mathbf{m} = \mathbf{0}$), misperceptions are zero in the presence of the signal ($\mathbf{b}(\mathbf{s}) = \mathbf{0}$), and consumers are fully attentive to pecuniary incentives ($\theta(\mathbf{s}) = 1$).

Proposition 1 also establishes the sufficient statistics an empiricist must identify to evaluate the policy. To identify the effect on consumer surplus, the ideal experiment needs to identify the Slutsky matrix, the vector of treatment effects to an information policy, *and* the vector of treatment effects to a fully informative signal. This result is intuitive: to evaluate the effect of an information policy on consumer well-being, we also need to know demand under full information as a benchmark for revealed preferences. To evaluate the effect on social welfare, we need additional information on firm markups and the marginal externalities of each product. Proposition 1 thus provides us with the recipe for our experimental design.

We now turn to the special case in which the social planner decides to use information in isolation (i.e., $\mathbf{\Delta t} = 0$).

Corollary 1. *The welfare effect of an information policy that changes the policy vector from $\rho = (\mathbf{0}', \mathbf{0}')$ to $\rho + \mathbf{\Delta}\rho = (\mathbf{0}', \mathbf{\Delta s}')$ is given by*

$$W(\mathbf{0}, \mathbf{\Delta s}) - W(\mathbf{0}, \mathbf{0}) \approx \mathbf{\Delta x}' \left(E^{-1}(\frac{1}{2}\mathbf{\Delta x} - \mathbf{\Delta x}^*) + \mathbf{m} - \epsilon \right). \tag{8}$$

If the policy is fully informative, the effect on welfare becomes

$$W(\mathbf{0}, \mathbf{\Delta s}^*) - W(\mathbf{0}, \mathbf{0}) \approx (\mathbf{\Delta x}^*)' \left(-\frac{1}{2}E^{-1}\mathbf{\Delta x}^* + \mathbf{m} - \epsilon \right). \tag{9}$$

The welfare effect of information is a function of how the designed signals change demand, $\mathbf{\Delta x}$, and how this change in demand is affecting informational and social frictions. As consumers do not take into account their effect on society when making choices, a fully informative signal is not generally optimal when no complementary taxes are used. Instead it may be more efficient to use less informative signals and to hide relevant information from consumers. This conflict of interest between the consumer and the social planner disappears in a perfectly competitive economy ($m = \mathbf{0}$) with no externalities ($\epsilon = 0$) such that the welfare-maximizing information policy is fully informative; $\mathbf{\Delta x} = \mathbf{\Delta x}^*$. Note that we are agnostic about how consumers update their beliefs and which type of signals the social planner can send to consumers. While this lack of structure is too unspecific to analyze strategic interactions, it offers a general framework for applied welfare analysis of any informational policy irrespective of the underlying game theoretic setting. For example, our results apply to situations in which the social planner can hide but cannot make up information as well as to those in which she can use deception to affect choices.

The social planner may also refrain from using information to steer choices and instead may decide to change relative prices. Corollary 2 answers the question of how an alternative tax policy affects efficiency. The corollary essentially reproduces results from previous work on the welfare effect of taxes when consumers make mistakes by O'Donoghue and Rabin (2006), Mullainathan, Schwartzstein, and Congdon (2012), Farhi and Gabaix (2020), and Allcott and Taubinsky (2015).

Corollary 2. *The welfare effect of a tax policy that changes the policy vector from $\rho = (\mathbf{0}', \mathbf{0}')$ to $\rho + \mathbf{\Delta}\rho = (\mathbf{\Delta t}', \mathbf{0}')$ is given by*

$$W(\Delta t, \mathbf{0}) - W(\mathbf{0}, \mathbf{0}) \approx \Delta t' E \left(\frac{1}{2} \Delta t - E^{-1} \mathbf{\Delta x}^* + m - \epsilon \right). \tag{10}$$

Denote an optimal tax vector in a tax policy by t^*. Then, an optimal tax vector is given by

$$\mathbf{t}^* = \left(E^{-1} \mathbf{\Delta x}^* - m + \epsilon \right). \tag{11}$$

If the social planner uses a tax policy in isolation, she needs to address three market failures per good (informational frictions, markups, and externalities) with one tax per good. The corrective intervention comes at the efficiency cost of $\Delta t' E \frac{1}{2} \Delta t$, which, again, is the classical Harberger distortion of taxation to consumer surplus in a previously untaxed market. The social planner therefore must balance the distortive effect of taxation with its corrective effect on market failures. Note that the optimal tax vector of a tax policy in isolation differs from the optimal tax vector of a policy mix. When both information and taxation are used, the crowding out of attention to taxes ($\frac{\partial \theta}{\partial s} < 0$) increases the size of the optimal tax. However, since information also affects misperceptions directly, it may decrease (increase) the optimal tax if information decreases (increases) misperceptions. It is therefore ambiguous whether taxes need to be larger or smaller when used in isolation. Note however, that a tax in isolation can achieve the same first-best outcome as a policy mix. The reason is that the social planner can fully correct all three market failures by setting each tax equal to the sum of the three marginal frictions in its respective market.

Finally, Proposition 1 and its corollaries provide a simple set of sufficient statistics to estimate the welfare effects of different policies in an empirical setting. Before we illustrate how this model translates to an experimental design, we briefly turn to the case in which informational frictions may be heterogeneously distributed among consumers.

Model with Heterogeneity

We extend our model by introducing heterogeneity in misperceptions. Let $\mathbf{b}$, $\mathbf{\Delta b}$ and ω follow a joint distribution function $G(\mathbf{b}, \mathbf{\Delta b}, \omega)$. Denote by $H(\mathbf{b}, \mathbf{\Delta b}|\omega)$ the joint distribution of $\mathbf{b}$ and $\mathbf{\Delta b}$ conditional on a state, such that $G(\mathbf{b}, \mathbf{\Delta b}, \omega) = H(\mathbf{b}, \mathbf{\Delta b}|\omega)F(\omega)$. We let $\Sigma_{\mathbf{\Delta x},\omega} = cov(\mathbf{\Delta x}|\omega)$ be the variance-covariance matrix of the vector of treatment effects to the information policy, conditional on a state of the world. Let $\mathbf{E}(i, j)$ be a matrix formed by replacing the i^{th} column of $\mathbf{E}$ by the j^{th} column of the identity matrix of $\mathbf{E}$. The welfare effect of a policy mix under heterogeneity and the optimal tax vector (conditional on a state of the world) are then given by Proposition 2.

Proposition 2. *Let* $\mathbf{b}$ *and* $\mathbf{\Delta b}$ *follow a conditional joint distribution function* $H(\mathbf{b}, \mathbf{\Delta b}|\omega)$*. Then, the welfare effect of a policy mix that changes the policy vector from* $\rho = (\mathbf{0}', \mathbf{0}')$ *to* $\rho + \mathbf{\Delta}\rho = (\mathbf{\Delta t}', \mathbf{\Delta s}')$ *is given by*

$$W(\mathbf{\Delta t}, \mathbf{\Delta s}) - W(\mathbf{0}, \mathbf{0}) \approx (\mathbf{\Delta t}'\mathbf{E} + \mathbb{E}[\mathbf{\Delta x}'|\omega]) \left(\frac{1}{2}\mathbf{\Delta t} + \mathbf{E}^{-1}\left(\frac{1}{2}\mathbb{E}[\mathbf{\Delta x}|\omega] - \mathbb{E}[\mathbf{\Delta x}^*|\omega]\right) + (\mathbf{m} - \epsilon)\right)$$
$$+ \underbrace{\sum_j \sum_i \frac{det(\mathbf{E}(i,j))}{det(\mathbf{E})} cov(\Delta x_i, \Delta x_j^*|\omega) + \frac{1}{2}Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x},\omega}]}_{\text{Additional term due to heterogeneity}}. \quad (12)$$

Denote an optimal tax vector in a policy mix under heterogeneity by $\mathbf{t}^*_{\mathbf{mh}}$*. Then an optimal tax vector satisfies*

$$\mathbf{t}^*_{mh} = \left(\mathbf{E}^{-1}\mathbb{E}[\mathbf{\Delta x}^*(\mathbf{s})|\omega] + \mathbf{m} - \epsilon\right)\theta(\mathbf{s})^{-1}. \quad (13)$$

Relative to the welfare effect under homogeneity in Proposition 1, we now require knowledge of the vector of expected demand responses to information. Furthermore, there are two additional terms that substantially complicate the empirical identification of welfare effects. The first term requires knowing all covariances between the treatment effects to the information policy and a fully informative policy. The second term requires knowing the entire variance-covariance matrix of the treatment effect to the information policy. As a result, the welfare effect of a policy mix can generally no longer be identified through aggregate demand elasticities to prices and information when misperceptions are heterogeneous. Identification would obviously be further exacerbated when we add heterogeneity in preferences and the tax salience parameter to the model. We empirically address the identification issue resulting from heterogeneity by analyzing treatment effects for particular subgroups of the sample as described in Section 5.4.

Another implication from Proposition 2 is that a fully informative policy will have larger benefits to consumers when misperceptions are heterogeneous. The reason is that heterogeneity in misperceptions creates an additional inefficiency: it is no longer guaranteed that identical consumers with equal valuations for a good buy the same quantity. This fact has been previously appreciated by Taubinsky and Rees-Jones (2017), who show that the benefits of de-biasing a consumer's inattention to sales taxes is higher when this inattention is heterogeneous. Corollary 3 highlights this insight.

Corollary 3. *The welfare effect of a fully informative signal in a previously unregulated market,* $\rho = (\mathbf{0}', \mathbf{0}')$*, is larger when misperceptions are heterogeneous. Specifically, the effect is given by*

$$W(\mathbf{0}, \mathbf{\Delta s}^*) - W(\mathbf{0}, \mathbf{0}) \approx \mathbb{E}[\mathbf{\Delta x}^{*\prime}|\omega] \left(\mathbf{m} - \epsilon - \frac{1}{2}\mathbf{E}^{-1}\mathbb{E}[\mathbf{\Delta x}^*|\omega]\right) - \frac{1}{2}Tr(\mathbf{E}\Sigma_{\mathbf{\Delta x}^*,\omega}). \tag{14}$$

To see formally that heterogeneity increases the welfare effect, note that since the Slutsky matrix is negative definite, $\mathbf{E}\Sigma_{\mathbf{\Delta x}^*,\omega}$ is semi-negative definite and its trace is weakly negative. It is strictly negative if treatment effects are heterogeneous and is equal to zero if treatment effects are homogeneous. Corollary 3 therefore provides the empirically testable prediction that the welfare effect of full information disclosure is larger with heterogeneity in misperceptions.

3 Field Experiment

3.1 Cooperation with Appliance Retailer

We partner with one of Europe's largest online retailers for domestic household lighting. As previously laid out, our experiment is motivated by the hypothesis that consumers undervalue the financial benefits from energy efficiency. The store's product range includes many energy-using durables related to lighting, such as living room and kitchen lamps, outdoor lighting, desk lamps, smart home appliances, and other products. The store has multiple websites in different languages and operates in the majority of European countries. We run our experiment in the German version of the store.

In the experiment, we provide consumers with less and more informative signals regarding the monetary savings associated with buying more energy efficient lighting technologies. In particular, there are four lighting technologies that can be ranked in descending order in terms of their energy efficiency: LED, CFL, halogen, and incandescent. Since more efficient technologies produce less externalities (e.g., in the form of lower CO_2 emissions), consumption choices may be subject to both informational frictions and uninternalized social costs. An optimal information policy is therefore not necessarily fully informative but weighs the benefits from more informed choices to consumer surplus with the associated change in externalities.

3.2 Design

The study was pre-registered at the AEA RCT registry.[7] Figure 1 illustrates the experimental design. Upon visiting the website of the online retailer, each visitor is randomly assigned to one of 15 groups with equal probability.[8] We use a 3×5 design where customers get randomized into three different informational groups (groups 1 to 3) and five different price discount subgroups (groups A to E). Visitors either see 1) a less informative signal, 2) a more informative signal, or 3) no information. In addition, every visitor receives a 20 percent price discount on a) LED bulbs, b) CFL bulbs, c) halogen bulbs, or d) incandescent bulbs or e) does not receive a price discount.[9] We use English translations of the treatments in the main part of the paper and show the original versions in German in the Appendix.

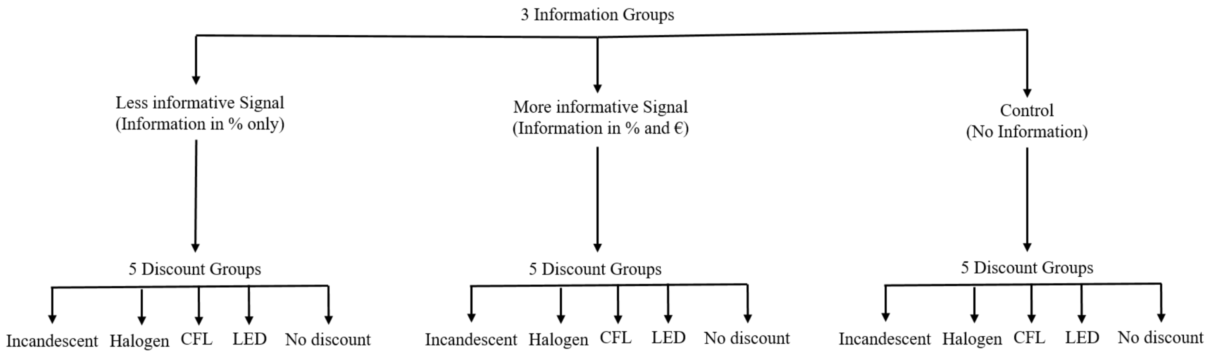
Information group 1 (less informative signal): For subjects in group 1, the banner in Figure 2 is displayed at the top of the browser and contains information on the annual electricity savings of three lighting technologies (LED, CFL, halogen) in comparison to a traditional 40W incandescent light bulb. We visualize the savings associated with each lighting technology by using a bar chart. In particular, subjects in this group are only informed about the savings of these light bulbs in *percentage* (e.g., a 4W LED saves 90 percent in electricity costs compared to the 40W incandescent). We do not inform subjects explicitly about how these relative savings in electricity costs translate into monetary savings. While the signal provides subjects with potentially useful information, it leaves substantial

[7]The trial ID is AEARCTR-0002814.

[8]Randomization is based on the visitor's HTTP cookie. If the visitor returns to the website multiple times, she stays in the same experimental group unless she actively deletes her cookies or changes the device. We provide evidence that that a change in cookies rarely occurred during the experiment.

[9]After subjects made their purchase decision, they were invited to participate in a survey. Due to low participation (N = 44), results from this survey cannot be used for any meaningful analysis.

Figure 1: Experimental Design: 3 × 5



Note: This figure illustrates the experimental design. Upon visiting the website, subjects get randomized into one of 15 experimental groups that vary in provided informational content and in prices.

room for interpretation. For instance, it may still be unclear for consumers whether 90 percent savings translate into 1 or 100 euros per year. Note that this information treatment is similar to labels that only provide a coarse relative ranking of the products' benefits. For instance, the EU energy efficiency label assigns grades ranging from "A" (most efficient) down to "E" (least efficient) but does not tell consumers the annual operating costs. By contrast, the US Energy Guide label both provides a relative ranking and informs consumers about each product's average annual operating cost.

Importantly, the banner appeared on every subpage of the website and could not be clicked away by the visitor. This makes it particularly likely that the visitor saw and engaged with the information. The only subpage where the banner did not appear was at the checkout when the visitor eventually made the payment.

Information group 2 (more informative signal): Figure 3 shows the banner with the more informative signal. Subjects see almost the same banner as subjects in group 1 but are also told how the savings in percentage translate into absolute savings in euros. Since individual savings may differ among consumers, the banner explicitly tells subjects the assumptions that were made when calculating the absolute savings. In particular, calculations are based on the average electricity price and the average level of light bulb utilization.

From classical economic perspective, this signal is (weakly) more informative, as it involves more potentially relevant information. It should therefore lead to more informed choices than the signal provided in group 1.

A potential concern of this treatment is that subjects do not properly process this information, possibly because they do not know how much they differ from the average consumer. Moreover, if information processing is costly, subjects could ignore the assumptions and just assume that the average savings correspond to their individual savings. We address these concerns in a second experiment and show that even after adjusting for individual heterogeneity in savings, information in this group moves savings beliefs closer to *individually* true savings than the information provided in group 1.

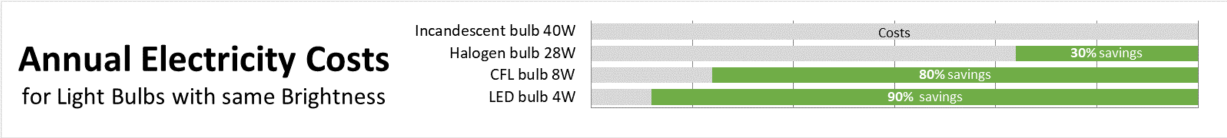
Note that we also left out other potentially relevant information that would have been difficult to convey in a concise way. One reason we did this is because the online store already provides many of the relevant information for each product. Next to every light bulb, the consumer can see the associated lifetime of the bulb, the energy consumption in watts, and the brightness of the bulb in lumens. More complex information such as calculated lifetime savings of each bulb would have required us to make strong assumptions on individual replacement behavior and to risk overwhelming or misinforming consumers.[10] It would have then been problematic to argue that information in group 2 leads to more informed choices than in group 1. Moreover, note that very informative energy efficiency labels, such as the Energy Guide label in the US, also only provide information on the annual operating costs and do not frame savings over the bulb's lifetime. Our treatments therefore provide a natural comparison between the less informative EU energy efficiency label that provides a relative ranking in school-type grades and the more informative US label that provides both a relative and an absolute ranking.

Information group 3 (no information): Subjects in this group receive no additional information on the financial benefits of energy efficiency, other than the information already provided by the online retailer in the product description.

Price discount groups: Each of the three informational groups is divided into five subgroups (A–E) in which we either offer subjects a 20 percent price discount on A) LED bulbs, B) CFL bulbs, or C) halogen bulbs, D) incandescent bulbs or E) no discount.

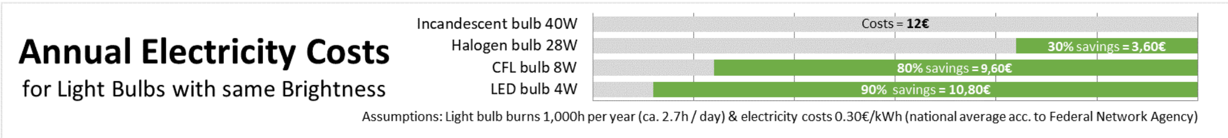
[10]For instance, if we had calculated the lifetime savings from purchasing a CFL instead of incandescent light bulb, we would have needed to make strong assumptions about the replacement behavior of the consumer. A CFL light bulb lasts roughly eight years, while an incandescent only lasts one year. Framing the energy savings in lifetime rather than annual savings and including replacement costs would have required us to assume a counterfactual of buying a CFL. One counterfactual could be that the subject buys eight incandescent light bulbs instead of one CFL. Another counterfactual could have been that the subject decides to buy four incandescent light bulbs and two halogen light bulbs (a halogen bulb last two years each in expectation). While the choice of any of these counterfactuals is already arbitrary, it would have been incredibly difficult to convey these assumptions to consumers within a banner.

Figure 2: Treatment: Less Informative Signal



Note: This figure shows an English translation of the banner that was used in the online store. For the original version in German see Figure A1.

Figure 3: Treatment: More Informative Signal



Note: This figure shows an English translation of the banner that was used in the online store. For the original version in German see Figure A2.

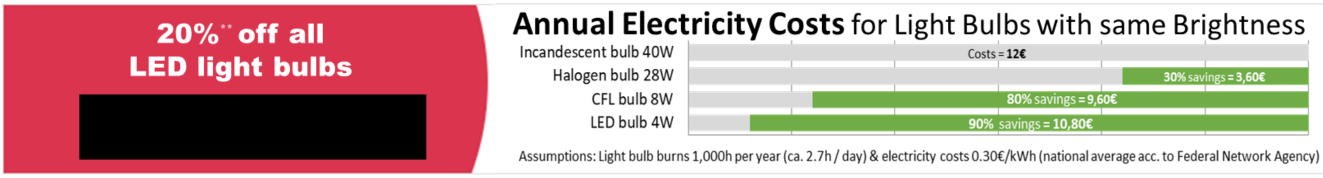
Figure 4: Treatment: Price Discount on LED Bulbs

Note: This figure shows an English translation of the banner that was used in the online store. For the original version in German see Figure A3. The black censor bars protect the company's anonymity.

This generates 15 experimental groups: 1.A, 1.B, 1.C, 2.A, . . . , 3.E. Figure 4 shows an example of the price discount on LED light bulbs. As an example of how we combined price and informational treatments, Figure 5 illustrates the combination of the more informative signal and a discount on LEDs. Here, the price discount is shown directly next to the informational intervention so that subjects who have seen the information should have also seen the individual discount. An overview of all 14 treatment screens in the original Version in German can be found in the Appendix. Figure A16 also illustrates how the banners were placed in the online store.[11]

[11]To protect the company's anonymity, we only show an excerpt of the online store.

Figure 5: Treatment: Combination of More Informative Signal and Price Discount on LED Bulbs



Note: This figure shows an English translation of the banner that was used in the online store. For the original version in German see Figure A11. The black censor bars protect the company's anonymity.

3.3 Taking the Model to the Field: Identification of Structural Parameters

Proposition 1 established the set of statistics we need to identify to estimate the welfare effect of an information policy, a tax policy, and a policy mix. In our experiment, the relevant outcome variables are quantities demanded of the four different lighting technologies such that $j \in \{LED, CFL, halogen, incandescent\}$. Recall that the researcher needs to identify the demand response to a signal policy, $\mathbf{\Delta x}$, the demand response to a fully informative signal, $\mathbf{\Delta x}^*$, and all own-price and cross-price demand derivatives (i.e., the Slutsky matrix, E). To evaluate a policy that uses both information and taxation, we also must know how much attention consumers pay to pecuniary incentives under information provision (i.e. $\theta(\mathbf{s})$).

We identify the vector of treatment effects to a partially informative signal policy by comparing demand for the four lighting technologies between the less informed group 1.E and the control group 3.E. This gives us an estimate of $\mathbf{\Delta x}$ from the theoretical model. To identify demand under full information, we assume that the more informative signal in group 3 fully informs consumers about the differences in energy costs. Under this assumption, comparing demand in group 2.E with 3.E identifies $\mathbf{\Delta x}^*$. Based on this assumption, we also refer to the more informative signal as fully informative.

We identify own-price and cross-price elasticities for the different lighting technologies by comparing demand responses across the different price discounts in group 3. This gives us an estimate of the Slutksy matrix. By comparing demand elasticities under the more and less informative signal with demand elasticities in the control group, we identify inattention to pecuniary incentives under less and more informative signals, denoted $\theta(\mathbf{s})$ and $\theta(\mathbf{s}^*)$, respectively.

3.4 Survey to Elicit Beliefs

To understand whether and how our treatments affected beliefs, we ran a survey in the same online shop and elicited savings beliefs under the different informational conditions.[12] Several months after the end of the first experiment, another banner (depicted in Figure A15) was shown on the website inviting consumers to take part in a three-question survey. Participation was incentivized with a discount of 20 percent on *all* light bulb technologies.

Upon clicking on the banner, subjects were randomized into one of three groups. Depending on their assignment, the first page of the survey displayed the following: S1) the less informative signal, S2) the more informative signal, or S3) no information. On the next page, participants were asked a question on their savings beliefs of LEDs relative to incandescent light bulbs, on their individual electricity price, and on their utilization habits of light bulbs. Responses to the first question allow us to identify the movement in savings beliefs induced by the information treatments. Answers to the second and third question inform us about the level of heterogeneity in savings: individual operating costs are calculated by (utilization in h) $\times$ (electricity price per kWh)$/1,000 \times$ watt of bulb. We therefore have a measure of how the subject's savings beliefs (responses to question 1) deviate from her *individually* true savings, based on self-reported numbers regarding the electricity price and utilization patterns. A limitation is that we were not able to incentivize responses such that results may involve measurement errors associated with hypothetical bias. With these potential limitations in mind, the survey may provide a useful indication for whether the underlying channel of the treatment effects to information is a change in savings beliefs.

3.5 Sample

We observe the number of times a subject visits the website and the date and time of each visit. In total, we record 1,193,773 website visits by 641,024 individually identified subjects within our experimental period of two months. This implies that the average subject made 1.9 visits during our experiment. 291 website visits were made using anonymized cookies that cannot be assigned to an individual user. These visits may be attributable to one or multiple individuals, and we therefore drop these observations. In total we observe 31,387 transactions by 28,811 subjects, meaning that around 4.5 percent of all subjects made at least one purchase. For every transaction, we know the time the purchase was made, the product choices, and the exact zip code to which the products were shipped.

We make the following restrictions to our main analysis. We exclude 253 subjects who purchased large bulk quantities and were likely to be firm employees rather than consumers. We define bulk quantities as the top 1 percent of light bulbs sales. Since our theory provides a

[12] We pre-registered the survey at the AEA RCT Registry under trial ID AEARCTR-0003122.

model of consumer behavior, we view the exclusion of bulk purchases as a plausible restriction to our analysis. Results from an analysis that includes bulk purchases are reported in the Appendix and yield qualitatively identical results.

Table A1 provides summary statistics for each experimental group. Every group includes roughly 43,000 subjects. The number of visits and purchase probabilities do not substantially vary across treatments. The third to fifth rows report the average light bulbs purchased from each technology, conditional on making a purchase. For example, in the more informative group without any price discount, the average customer who made a purchase bought 0.51 LED bulbs. Put differently, approximately every second consumer purchased one LED, on average. The first remarkable result is that even in the control group, most customers already purchase the most energy-efficient technology. The average customer in the control group purchases 0.51 LEDs, 0.015 CFLs, 0.10 halogen bulbs, and 0.09 incandescents. This means that, on average, only every 67th customer buys a CFL, every 10th a halogen, and every 11th an incandescent bulb. These numbers are surprising in the light of the extensive discussion in the literature and policy debates that customers apparently underinvest in energy efficiency. While this might be specific to our sample, recall that our retailer is one of Europe's largest appliance retailers for household lighting. In Section 6, we furthermore provide evidence that purchasing behavior in the same shop used to be dramatically less energy efficient only five years ago.

We also have data on the order's shipping time, whether the transaction was pre-paid, and whether the customer wanted a printed invoice included in the shipped package. All of the statistics do not seem to differ between treatment arms.

4 Reduced-Form Results

4.1 Probability to Purchase at the Store

We first report differences across treatments in the likelihood to purchase at the store. We run the following probit regression:

$$Pr(Purchase_i = 1|T_i, DAY_i) = \Phi(\lambda' T_i + \gamma' DAY_i), \tag{15}$$

where $Pr(Purchase_i = 1|T_i, DAY_i)$ is the probability that subject i makes at least one purchase during the time of the experiment and $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution. T_i is a vector of indicators for each of the treatment groups, where each indicator takes on the value of one if subject i is in the respective treatment group. The omitted experimental group is the control group. We run two separate regressions: one in which we pool the information and price treatments and one in which we also analyze all interactions between informational and pecuniary incentives. Since subjects can make multiple purchases, we code the dummy vector DAY_i such that an element equals one if the *first* purchase of the subject was made during a particular day and equals zero otherwise.

Table 1: Average Treatment Effects on Purchase Probability

	Probability to purchase
Information treatments:	
More informative	–0.0008
	(0.0006)
Less informative	–0.0003
	(0.0006)
Price discounts:	
LED	0.0007
	(0.0008)
CFL	0.0005
	(0.0008)
Halogen	0.0011
	(0.0008)
Incandescent	–0.0002
	(0.0008)
Baseline probability	0.0446
N	640,771

Note: The table shows average marginal effects from a probit regression of 1(Purchase) on pooled treatment variables. Day fixed effects are included. Standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table 1 reports the marginal effects from the probit regression in equation 15 where informational and price groups are pooled. In the control group 4.5 percent of individual visitors made at least one purchase. Neither the informational nor the pecuniary treatments seem to have affected these probabilities. All coefficients are economically small and statistically insignificant. This suggests that the treatments did not cause selection into purchasing at the store such that differences in purchasing behavior conditional on buying at the store have a causal interpretation. Table A2 in the Appendix shows the regression including interaction effects between information and price treatments and yields the same conclusion.

4.2 Demand for Lighting Technologies

We proceed by analyzing how treatments affect the number of purchased light bulbs with technology $j \in \{$ LED, CFL, halogen, incandescent$\}$ conditional on making a purchase. We run the following OLS regression for the first purchase a customer made:

$$y_{ij} = \alpha_j + \tau_j' T_i + \psi_j DAY_i + \nu_j ZIP_i + \epsilon_{ij}, \tag{16}$$

where y_{ij} are quantities purchased of light bulb technology j by consumer i during her first purchase. ZIP_i is an indicator vector for the customer's zip code during the first purchase.

Table 2 provides results from the four regressions of quantities demanded on the pooled treatments. The columns are ordered from left to right in descending order with respect to the energy efficiency level of the bulbs. The first six rows show the informational treatments and price discounts, and the last two rows show baseline demand and sample size.

Again, we can see that baseline demand for less efficient light bulbs is extremely low relative to demand for LED bulbs. The average consumer buys 0.43 LEDs, 0.01 CFLs, 0.08 halogen, and 0.02 incandescent bulbs. The more informative signal has an economically large and statistically significant negative effect on LED demand. The signal decreased demand for LEDs by 0.06, or 13.3 percent relative to baseline, and this effect is significant at the 5 percent level. We also observe a negative effect on demand for the least-efficient technology, as incandescent demand falls by 0.01, or 58 percent. The more informative signal seems to partially move consumer choices to the medium-efficient technology as CFL demand increases by 0.01, which is a relative treatment effect of almost 90 percent.

The coefficients of the less informative signal are not statistically significant in this pooled regression model. Recall that the two informational treatments only slightly differed in terms of content. The large difference in the coefficients therefore appears remarkable and implies that the monetary information had a strong additional effect.

Despite the high relative baseline demand for LEDs, we find a strong positive effect of a price discount on demand. The 20 percent price discount increased demand by 22.4 percent (or 0.1 units), implying a large own-price elasticity of –1.02. The effect is statistically significant at the 1 percent level. Looking at the price coefficients for the other three technologies, we do not find statistically significant effects.

Table A4 shows results from the same regressions but with follow-up purchases included and standard errors clustered on the individual level. The results are qualitatively the same for LED demand but are quantitatively slightly different: the effect of the more informative signal on LED demand is slightly smaller (–9.7 percent), whereas the effect of the LED

Table 2: Average Treatment Effects on Demand – First Purchase Only

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.057**	0.010**	–0.004	–0.011*
	(0.025)	(0.005)	(0.011)	(0.007)
Less informative	–0.015	0.001	–0.013	–0.008
	(0.025)	(0.004)	(0.011)	(0.006)
Price discounts:				
LED	0.096***	–0.009	0.006	0.001
	(0.033)	(0.006)	(0.014)	(0.008)
CFL	0.039	–0.005	0.010	0.004
	(0.032)	(0.007)	(0.013)	(0.008)
Halogen	–0.039	–0.007	0.015	0.002
	(0.031)	(0.006)	(0.013)	(0.009)
Incandescent	–0.009	–0.005	0.011	–0.002
	(0.031)	(0.007)	(0.013)	(0.008)
Control group mean	0.428	0.011	0.079	0.019
N	28,553	28,553	28,553	28,553

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on pooled treatments. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

subsidy is larger (27 percent). The negative effect on incandescents remains unchanged, while the positive effect on CFL demand disappears.

Table A3 provides the fully interacted regression models for first purchases. The treatment group that only received the more informative signal still has a negative but smaller and insignificant coefficient for LED demand of –0.027 (or –6.3 percent). The largest negative coefficient on LED demand of –0.05 can be found when the more informative signal is combined with a discount on halogen light bulbs. The positive effect on CFL demand mostly comes from the treatment group in which the more informative signal is presented in isolation. Here, CFL demand increases by 300 percent relative to baseline, albeit from a low baseline demand.

The less informative signal presented in isolation has a positive impact on LED demand of 0.10 (or 23.5 percent), which is significant at the 10 percent level. The LED discount without any informational intervention has a particularly large effect of 0.18, which is larger than the average effect of 0.11 from the pooled model.

We also observe some surprising effects of the CFL discount on the demand as both CFL and incandescent demand increase. While this may suggest that these products are complements, it may also be a result of the low baseline demand for less energy-efficient alternatives that may increase the probability of false positives. In a next step we increase robustness against small cell variation by summing up demand for CFLs, halogen, and incandescent light bulbs and create one outcome variable that we call demand for "Non-LED bulbs". We repeat the OLS regression with demand for Non-LED bulbs as the outcome variable. Table A5 shows the results and shows that the cross-price elasticity between LEDs and Non-LEDs is still positive. The own-price elasticity for Non-LEDs is marginally significant and notably smaller than the own-price elasticity of LEDs. Furthermore, both the more informative and less informative signal have relatively large positive coefficients for demand for Non-LED bulbs, yet are statistically insignificant.

4.3 Effect on Beliefs

The standard interpretation of the treatment effects resulting from information provision is that the underlying channel of the demand responses is a shift in subjects' beliefs. To test whether our treatment effects are in line with this interpretation, we compare differences in savings beliefs between survey respondents from the second experiment in the different treatment groups. In total, 765 subjects participated in the survey. Depending on the treatment assignment, subjects first see the more or the less informative signal or no information at all. They are then asked the following question to elicit their savings beliefs:

Q1: "How many euros would you save in annual electricity costs if you used a 4W LED light bulb instead of a 40W incandescent light bulb? Please state the annual electricity savings in euros."

Table 3 reports results from an OLS regression of savings beliefs on the informational treatments. We exclude outliers that reported savings beliefs larger than the 95th percentile of 265 euros per year. Over 77 percent in the control group report electricity savings larger than the average savings of approximately €11. The average consumer in the control group believes to save €52.71 per year. In line with the reduction in LED sales, providing consumers with the more informative signal shifts savings beliefs downwards. The less informative signal also moves beliefs, albeit into the opposite direction. This shift is in line with the positive treatment effect coefficient of the less informative signal on LED demand observed in Table A3. The average treatment effects of the less and more informative signal are significant at the 5 percent and 10 percent level, respectively. Interestingly, the coefficients are almost identical in absolute terms: the more informative signal decreases expected annual savings by €9.53, whereas the less informative signal increases estimated savings by €9.20.

A concern regarding the interpretation of the results is whether the more informative signal has moved consumers' beliefs closer to their *individually* true savings. After all, the information only tells subjects the savings of the *average* consumer, which may differ from individual savings. Since households have different consumption patterns and energy prices, we asked them the following two additional questions:[13]

Q2: "How many cents, do you think, are you paying per kilowatt hour? Please enter a number in cents."

Q3: "How many hours are you using a light bulb on average per day? Please enter a number in hours."

The answer to questions 2 and 3 allow us to calculate the *individually* true savings of a subject and then compare these to their savings beliefs using the response to question 1. We create the variable "bias in beliefs" by subtracting the individually true savings we calculated from the subject's savings belief. If the difference is zero, savings beliefs equal true savings, and the subject is correctly informed. A positive (negative) difference implies an overestimation (underestimation) of the savings. Figure 6 plots the empirical CDFs of this difference for the three experimental groups. Most consumers in the control group overestimate the savings, and this overestimation exacerbates with the less informative signal. The distribution of belief distortions for subjects who saw the more informative signal is shifted toward zero relative to the control group. These results make us confident that the more informative signal, in fact, led to more informed choices than the alternative treatment that only provided information on the relative savings.

As another robustness test, we do an additional exercise that addresses the following question: if consumers in the more informative treatment (falsely) assume that their consumption is equal to the average consumer, by how much are we inducing additional bias in the savings beliefs? The bin scatter plot in Figure 7 answers this question by plotting the control group's relative heterogeneity in savings versus the heterogeneity in the belief bias. Relative savings heterogeneity is defined as the deviation of individual savings from the

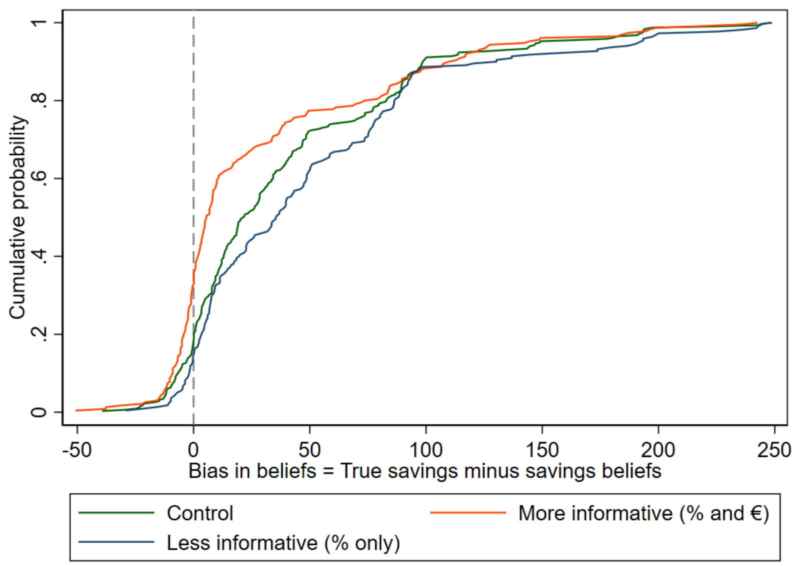
[13]Figures A17, A18, and A19 in the Appendix show the cumulative belief distributions for each of the three questions.

Table 3: Effect on Savings Beliefs

	Estimated savings (in euros)
More informative	–9.529**
	(4.623)
Less informative	9.200*
	(4.968)
Control group mean	52.713***
	(2.959)
N	765

Note: The outcome variable is the consumer's estimated annual electricity savings (in euros) of a 4W LED bulb relative to a 40W incandescent bulb in the post-experimental survey. Results are from an OLS regression of savings beliefs on the informational treatments. To account for outliers, only subjects with savings beliefs below the 95th percentile are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

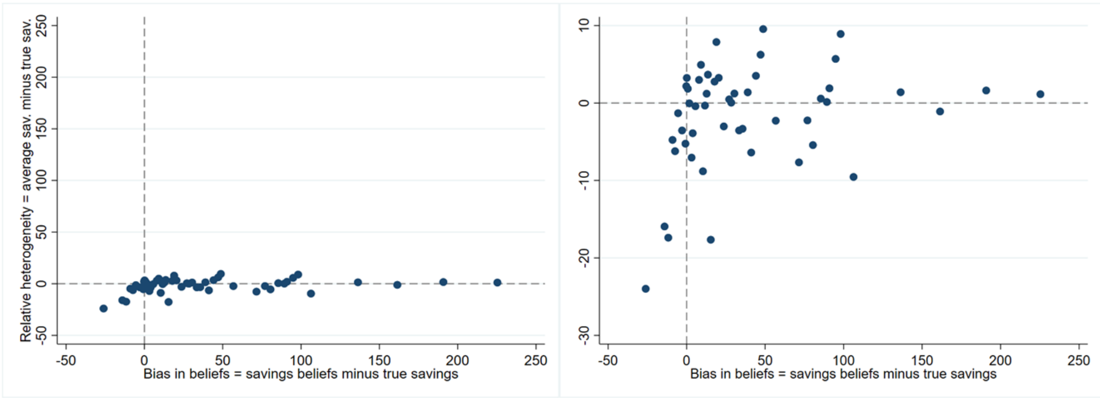
Figure 6: Bias in Savings Beliefs



Note: The figure shows the empirical cumulative distribution functions of the error in savings belief, for each experimental group. We calculate the error as the difference between consumer's answer to the savings belief question and the individually true savings that we calculate using the individual's reported electricity price and utilization of a light bulb. If consumer beliefs equal their true savings, the error is zero. To account for outliers, only subjects with savings beliefs below the 95th percentile are included.

savings of the average consumer. If subjects just assume the information provided in the more informative signal reflect their individually true savings even though they are not the average consumer, then this difference measures the bias that the more informative signal

Figure 7: Relative Savings Heterogeneity versus Heterogeneity in Belief Bias



a) Same axis length

a) Zoomed in on ordinate

Note: The graphs plot the error in savings belief against the relative heterogeneity in savings for the control group of the survey experiment. Relative heterogeneity is defined as average savings (= €10.80) minus individually true savings. Panel a) holds both axes at the same minimum and maximum to compare the relative magnitude of heterogeneity in savings and in beliefs. Panel b) zooms in on the ordinate.

would induce. The abscissa again shows the deviation between subjects' savings beliefs and individually true savings. The plot can therefore be interpreted as showing by how much the more informative signal could induce bias versus by how much it reduces bias.

Panel A of Figure 7 holds the minimum and maximum of both axes at the same level to provide a fair comparison of the magnitudes. This makes apparent that even if consumers are completely naive and just assume their savings correspond to the average savings, they are still likely to be better off than without the provision of the more informative signal. Panel B zooms in on the ordinate to get a better idea of the absolute dispersion of relative heterogeneity. Most consumer savings only deviate by around +10/−10 euros from the savings of the average consumer. By contrast, most of the distortion in savings beliefs for untreated subjects lies between −10 and 100 euros. Thus, even in the extreme case in which consumers are completely naive, the more informative signal is likely to lead to more informed choices.

5 Structural Estimates and Welfare

5.1 Moment Conditions and Model Constraints

We estimate the sufficient statistics from equation 1 by jointly estimating the system of demand equations with a two-step GMM estimator. To increase power and the reliability of the point estimates, we continue to pool all non-LED technologies into one category such that we have two technologies $j \in \{\text{LED, Non-LED}\}$. We therefore have two price discounts

$d \in$ {LED, Non-LED} and three informational groups $s \in \{$ c, l, m$\}$, where c represents no information (control group), l the less informative signal, and m the more informative signal. For the Non-LED bulbs, we calculate the price discount by taking the average of the three price discount for CFLs, halogen and incandescent bulbs.[14]

Let P_i^s be a 2×1 vector of price discounts where any element of the vector equals the monetary reduction in price subject i has received for product j under informational treatment s. We let $P_i = (P_i^{c\prime}, P_i^{l\prime}, P_i^{m\prime})'$ denote the 6×1 vector containing all price discounts in each informational state. Denote ξ_{js}^k as the constant demand derivative of light bulb technology j with respect to a price change in technology k when information policy s is provided. Within each informational state, there are two parameters for every j, and we list these in the 2×1 vector ξ_{js}. The tax salience parameter is θ_z for $z \in \{l, m\}$.

Further, let τ_j be the 2×1 vector of demand responses of product j to the informational treatments. We denote the 2×1 vector indicating whether subject i was in any of the informational groups by I_i.

For every lighting technology j, there are six moment conditions for the demand slopes,

$$\mathbb{E}[P_i \left(y_{ij} - \xi_{jc}' P_i^c - \theta_m \xi_{jc}' P_i^m - \theta_l \xi_{jc}' P_i^l - \tau_j' I_i \right)] = 0 \tag{17}$$

and two moment conditions for the informational treatments,

$$\mathbb{E}[I_i \left(y_{ij} - \xi_{jc}' P_i^c - \theta_m \xi_{jc}' P_i^m - \theta_l \xi_{jc}' P_i^l - \tau_j' I_i \right)] = 0. \tag{18}$$

Note that the moments impose the theory-driven constraints on the own-price and cross-price demand slopes between informational treatments:

$$\xi_{k,\text{ c}}^j = \theta_{\text{m}} \xi_{k,\text{m}}^j \tag{19}$$

$$\xi_{k,\text{ c}}^j = \theta_{\text{l}} \xi_{k,\text{l}}^j. \tag{20}$$

The theoretical model also requires us to restrict the Slutsky matrix to be symmetric within each informational state:

$$\xi_{js}^k = \xi_{ks}^j. \tag{21}$$

With one additional moment condition for demand in the control group, this means we

[14]We calculate the absolute price reduction for every light bulb technology by multiplying the 20 percent discount for a technology by the median price of that technology. We take the median instead of the mean to account for a few decorative products with extremely high prices.

have 9 moment conditions per technology. In total, we therefore have 18 moment conditions to estimate 11 parameters. We use the two-step GMM estimator to find the optimal weight matrix.

5.2 Structural Parameter Estimates

Table 4 shows the results of the structural estimation described in the previous section. The own-price derivative of demand is about –0.09 and –0.08 for LED and Non-LED, respectively. Both coefficients are statistically significant at the 1 percent level. The cross-price derivative is –0.02 and significant at the 10 percent level, again suggesting a complementarity between LEDs and less energy-efficient alternatives. The more informative signal slightly reduces demand for LEDs by 0.04, albeit not statistically significantly. By contrast, we find an increase in demand for Non-LED bulbs of 0.04 that is significant at the 10 percent level. The less informative signal again has a positive and statistically significant effect on LED demand by 0.08.

The parameters that indicate the salience of pecuniary incentives are far below one for both informational treatments, suggesting that demand elasticities decrease when information is provided. The salience parameters equal 0.56 and 0.38 for the more and the less informative signal, respectively. In other words, demand elasticities fall by 44 percent and 62 percent when information is provided, making financial incentives less effective.

At the lower part of the table, we report the calculated misperception that directly result from the structural point estimates. The average consumer overvalues LEDs by 56 cents per bulb (around 6 percent of the sales price) and undervalues less efficient alternatives by 67 cents per bulb (around 17 percent of the sales price). Providing consumers with the less informative signal exacerbates the overvaluation for LEDs and slightly decreases the undervaluation for less efficient alternatives. After consumers are treated with the less informative signal, they overvalue LEDs by 1.43 euro per bulb and undervalue less efficient alternatives by 50 cents. Note that this implies that moving from no information to an information policy that shows savings information in percentage makes consumers worse off. This is hard to reconcile with the notion of fully rational Bayesian consumers, as information disclosure should always make consumers weakly better off (Kamenica and Gentzkow 2011).

Table 4: Structural Parameters

	LED	Non-LED
Demand slopes (dx/dp):		
LED	–0.094***	–0.020*
	(0.018)	(0.012)
Non-LED	–0.020*	–0.077***
	(0.012)	(0.027)
Demand responses to information (Δx):		
More informative	–0.040	0.040*
	(0.035)	(0.022)
Less informative	0.084**	0.029
	(0.034)	(0.022)
Tax salience with information provision (θ_n) :		
θ_{abs}	0.551***	
	(0.171)	
θ_{rel}	0.384**	
	0.177	
N	28553	
Misperceptions (in €per light bulb):		
b_{LED}	–0.56	
$b_{non-LED}$	0.67	
Misperception after provision of less informative signal:		
b_{LED}	–1.43	
$b_{Inefficient}$	0.50	

Note: The upper part of the table shows GMM estimates from the two-step GMM estimator using the moment conditions specified in the main text. All variables are de-meaned on the zip code level. "Non-LED" is a variable that pools quantities purchased of products with a non-LED technology: CFL, halogen, and incandescent. The bottom part of the table displays the information frictions that result from the GMM estimates, as described in the theoretical part. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

5.3 Welfare Effects

In our welfare evaluation we abstract from interactions with other existing policies to keep the analysis simple and close to the theoretical model.[15] Using results from Table 4 then suffices to approximate the effect of information and tax policies on consumer surplus. For the overall welfare effect, we need additional information on marginal markups and externalities. The company provided us with detailed data on the gross margin of each light bulb technology,

[15]Other existing regulatory policies include energy efficiency standards, electricity taxes, and an emissions trading scheme.

calculated as the pre-tax retail price minus the buying price and minus any discounts given to customers. We consider this number an approximation to firm markups because it does not include fixed costs and marginal labor costs of selling a bulb are locally zero for this store.

To calculate externalities, we assume a social cost of carbon of USD 35 per ton of CO_2 (Nordhaus 2018). Domestic electricity consumption in Germany produces around 518g of CO_2 per kWh (German Environment Agency 2019). This translates into a social cost of electricity consumption of approximately USD 0.02 per kWh, similar to figures used in the related literature (e.g., Houde and Aldy 2017). To convert this into euros, we use an exchange rate of USD/EUR = 0.9. The average LED offered in the store uses 5W and the average German household uses a light bulb for around 1,000 hours per year. We calculate externalities over 15 years, which is the expected lifetime of an LED bulb. These assumptions result in a marginal externality of 1.35 ($= 5 \times 0.02 \times 0.9 \times 15$) euros per LED. The average Non-LED bulb uses 69W and lasts 3.7 years. The marginal externality of such a bulb is therefore 4.60 ($= 69 \times 0.02 \times 0.9 \times 3.7$) euros. Since 4.05 Non-LEDs need to be purchased over 15 years, the assumed counterfactual external damage to buying one LED equals 18.61 euros.

Table 5 reports the effect of different policies on consumer surplus, firm profits, externalities, and social welfare. All numbers are interpreted in euros per consumer, where we define a consumer as one of the 28,533 subjects who made at least one purchase at the shop.

Table 5: Welfare Estimates Assuming Homogeneity

Policy	Δ Utility (€/consumer)	Δ Profits (€/consumer)	Δ Externalities (€/consumer)	Δ Welfare (€/consumer)
More informative signal	0.02	0.13	0.69	–0.54
Less informative signal	–0.07	0.49	0.66	–0.24
Optimal tax: $t_{led} = –1.54$ €/bulb, $t_{Inef} = 2.26$ €/bulb	–5.11	–5.85	–15.55	4.60

We can see that an information policy that attempts to fully inform consumers increases consumer surplus by around 2 cents per customer. Firms gain 13 cents per consumer from this policy. Due to the strong reduction in demand for energy-efficient LEDs, externalities increase by 69 cents per consumer. This means that the external damage from this policy is 360 percent larger than the total benefit to consumers and firms. Summing up all efficiency effects, the welfare reduction amounts to 54 cents per consumer, or 15,419 euros in the entire sample of shop customers. Reducing the informativeness of the signal by hiding relevant information on absolute savings increases economic efficiency. While every consumer loses 7 cents in utility from this policy as it increases informational distortions, firms and society as a whole benefit. Firm profits increase substantially by 49 cents per consumer, which might explain why retailers rarely advertise the absolute savings voluntarily in Germany. Externalities increase overall because consumers purchase more of both LEDs and less energy-efficient alternatives. The increase in externalities is, however, smaller than under the more informative policy. In a nutshell, partial information disclosure is more efficient than full information disclosure but still decreases overall welfare.

The last row illustrates how the optimal tax policy compares to information policies. The optimal tax vector involves a large tax on less efficient alternatives of 2.26 euros per bulb and a sizable subsidy on LEDs of 1.54 euros per bulb. The losers of this policy are consumers and firms; the average consumer loses 5.11 euros in utility, and firm profits are reduced by 5.85 euros per consumer. Yet, the optimal tax policy is the most efficient policy tool, as it yields a large reduction in externalities of 15.55 euros per consumer and thereby increases overall welfare by 4.60 euros per consumer. Summing this up for our sample, welfare increases by 131,252 euros. Since externalities are the most important market friction in our setting, an optimally calibrated tax vector yields significantly larger welfare gains than any information policy since taxes can be set such that they address all three market failures. Steering behavior through information only is more difficult, and it is hard to think of an informational intervention that yields a demand response large enough to correct all three market failures in our setting.

Recall the theoretical result that in the current framework an optimal tax policy in isolation has the same welfare effect as an optimal policy mix. However, the respective optimal tax vectors may not be equal. Table 6 shows the optimal tax policy in isolation and in combination with informational interventions. Since information crowds out cognitive attention to monetary incentives, taxes and subsidies are the lowest when no information is provided. The optimal subsidy on LEDs increases to 2.79 euros and 1.75 euros per bulb when the more and less informative signal is implemented, respectively. Taxes on less efficient alternatives increase to 4.11 euros and even 6.32 euros per bulb. Under the assumption that preferences and informational frictions are homogeneous, any of these three policies will cause the same effect on welfare.[16]

[16] One assumption driving this result is that we assume no additional inefficiencies in the revenue recycling process. If in reality some tax revenue is lost in the recycling process, the welfare increase of a policy mix is smaller than the increase from an isolated tax policy.

Table 6: Optimal Taxes

Policy	Tax on LED bulbs (€/bulb)	Tax on Non-LED (€/bulb)
Tax policy in isolation	–1.54	2.26
Policy mix with more informative signal	–2.79	4.11
Policy mix with less informative signal	–1.75	6.32

5.4 Heterogeneity

Heterogeneity in informational frictions and preferences may change our results. For instance, one could imagine that information is better at targeting consumers with informational frictions, while taxes are more effective in correcting externalities. We now turn to the case in which consumers are heterogeneous as previously analyzed in the theoretical framework.

Structural Parameters and Welfare Effects with Heterogeneity

We empirically address the issue of latent heterogeneity by analyzing treatment effects separately for subgroups of the sample based on observables. We based the choice of observables on findings from the literature and included them in the pre-registration. This approach requires the strong assumption that, based on observables, we can split the sample into subgroups in which informational frictions (and preferences) are approximately homogeneous. The effect on consumer surplus is then identified by taking the average of the effect for each subgroup.

We match the customers zip code with publicly available data on income and vote shares for Germany's major environmental party ("Die Grünen").[17] These variables are motivated by previous literature that has found higher levels of attention to energy costs among consumers with higher income (Houde and Aldy 2017) and stronger environmental preferences (Allcott, Knittel, and Taubinsky 2015). Our data source on income and votes does not provide us with information for every five-digit German zip code. To reduce the loss of observations, we merge data on the basis of the first four (instead of five) digits of a zip code. This leaves us with 21,879 observations with available income data and 21,467 observations with political preferences.

To see whether these sample restrictions already yield different results, we first calculate the welfare effects under homogeneity again using only data from the subsample. Table

[17]Both data sets are publicly available. Income data come from the Institute of Economics and Social Sciences (Wirtschafts- und Sozialwissenschaftliche Institut) and voting data from the German Bundestag.

A7 (Table A8) presents the structural estimates (the welfare effects) for the subsample for which we have available income data, still assuming that misperceptions and preferences are homogeneous. The results are qualitatively identical to the ones from the entire sample but differ in magnitude. The more informative signal now has a larger negative welfare effect of –0.86 (versus –0.54) euros per consumer and the optimal tax vector a smaller positive benefit of 3.82 (versus 4.60) euros per consumer. The less informative signal has approximately the same effect for the subsample (–0.23 euros per consumer) as for the entire sample (–0.24 euros per consumer). Table 7 reports the structural estimates for consumers from zip codes with below- and above-median income, separately. Point estimates suggest that demand for LEDs is slightly more price elastic for low-income households, even though the difference in points estimates is not significant. High-income households are significantly more price elastic to Non-LEDs than low-income households. In terms of demand responses to information, we see that the increase in less energy-efficient light bulb sales caused by the more informative signal is mainly attributable to high-income households. Furthermore, the less informative signal significantly increases demand for LEDs among both income groups.

Low-income households are remarkably inattentive to the financial incentive when paired with information. The parameter $\theta_m = 0.35$ implies that the demand response to discounts is approximately three times higher when the incentive is provided without information instead of in combination with the more informative signal. The attention parameter is even lower when the incentive is combined with the less informative signal ($\theta_l = 0.20$), albeit not significantly different to θ_m. By contrast, high-income households are substantially more attentive to incentives under both informational interventions. Both attention parameters are statistically indistinguishable from one such that we cannot reject the hypothesis that high-income households are fully attentive to the incentives when coupled with information.

The misperception matrix in the bottom part of the table indicates that both income groups undervalue the financial benefits of energy efficiency. While both consumer groups undervalue LEDs by 0.87 euros per bulb, low-income households overvalue less efficient alternatives more than high-income households (1.49 versus 1.10 euros per consumer). The less informative signal exacerbates the overvaluation of LEDs and reduces the overvaluation for less energy-efficient alternatives. This is true for both income groups, albeit different in magnitude. Partial information disclosure increases high-income households' overvaluation of LEDs to 2.13 euros per bulb, an increase of 145 percent. Low-income households' overvaluation increases by 100 percent to 1.74 euros per bulb. By contrast, the undervaluation of Non-LEDs decreases by 8 percent for high-income households but by 56 percent for low-income households.

Welfare effects are reported in Table 8. Full information disclosure increases consumer surplus by 0.06 and 0.10 euros per consumer for low- and high-income households, respectively.

Table 7: Structural Estimates: Heterogeneity in Income

	Low-income households		High-income households	
	LED	Non-LED	LED	Non-LED
Demand slopes (dx/dp):				
LED	–0.127***	–0.011	–0.099***	–0.044
	(0.030)	(0.016)	(0.025)	(0.020)
Non-LED	–0.011	–0.026	–0.044	–0.166***
	(0.016)	(0.032)	(0.020)	(0.051)
Demand responses to information ($\Delta_n x$):				
More informative	–0.094*	0.028	–0.038	0.144***
	(0.054)	(0.027)	(0.059)	(0.042)
Less informative	0.120**	0.031	0.128**	0.070*
	(0.056)	(0.028)	(0.057)	(0.041)
Tax salience with information (θ_z) :				
θ_m	0.354		0.805***	
	(0.244)		(0.176)	
θ_l	0.202		0.781***	
	0.241		0.176	
N	10965		10977	
Misperception (in €per light bulb):				
b_{LED}	–0.87		–0.87	
$b_{Non-LED}$	1.49		1.10	
Misperception after provision of less informative signal:				
b_{LED}	–1.74		–2.13	
$b_{Non-LED}$	0.65		1.01	

Note: The sample is split by median income. Estimation techniques and calculations are the same as in Table 4 but are separate for each income group. Only subjects from zip codes with available data on average income are included. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

In line with Corollary 3, the average effect on consumer surplus under heterogeneity (0.08 euros per consumer) is larger than under assumed homogeneity (0.07 euros per consumer in Table A8). High- and low-income households lose equally from partial information disclosure (–0.12 euros per consumer). Just as in the case of homogeneity, both informational interventions reduce welfare as the increase in environmental externalities remains large.

The optimal tax vector involves both a slightly lower subsidy and tax than under homogeneity. Importantly, the burden of this tax vector is mostly borne by high-income households. The decrease in utility of 10.39 euros per high-income consumer is approximately 5.8 times

Table 8: Welfare Effects with Heterogeneity in Income

Policy	Δ Utility Low-income consumers (€/consumer)	Δ Utility High-income consumers (€/consumer)	Δ Profits (€/consumer)	Δ Externalities (€/consumer)	Δ Welfare (€/consumer)
More informative signal	0.06	0.10	0.35	1.52	–1.09
Less informative signal	–0.12	–0.12	0.77	1.11	–0.46
Optimal tax: t_{led} = –1.23 €/bulb, t_{Inef} = 1.64€/bulb	–1.80	–10.39	–7.13	–18.47	5.24

Note: The sample is split by median income to calculate consumer surplus for each income group. "Low-income" and "high-income" consumers are defined as subjects from regions with an average income below and above the sample median, respectively. Only subjects from zip codes with available data on average income are included.

larger than for low-income consumers. The reason for this is that even though low- and high-income consumers have similar misperceptions, high-income consumers' demand for Non-LEDs is substantially more price elastic. A tax on these products therefore causes high-income households to forgo the consumption of many Non-LED quantities. By contrast, low-income consumers respond relatively little to taxes on inefficient products, as both own-price and cross-price elasticities are smaller.

The general conclusion that taxes dominate both informational interventions remains valid under heterogeneity, as welfare increases by 5.24 euros per consumer with the optimal tax vector. Table 9 highlights that taxes on less efficient alternatives need to be substantially larger in a policy mix with information than in isolation. Subsidies for LEDs need to be larger when paired with full information provision but smaller when combined with partial information disclosure.

Table 9: Optimal Taxes with Hetereogeneity in Income

Policy	Tax on LED bulbs (€/bulb)	Tax on Non-LED (€/bulb)
Tax policy in isolation	–1.23	1.64
Policy mix with more informative signal	–2.50	3.18
Policy mix with less informative signal	–0.87	6.89

Note: The table shows the optimal tax vector under heterogeneity given that income groups identify preference and belief heterogeneity.

Tables A9–A13 report results for the subsample for which data on vote shares for the environmental party is available. We assign each subject to the group of "green consumers" and "non-green consumers" based on whether she comes from a region with above- or below-median support for the Green party. Non-green consumers have larger (structural) misperceptions of energy efficiency. They overvalue LEDs by around 1.25 euros per bulb and undervalue Non-LEDs by 2.62 euros per bulb. Green consumers undervalue LEDs by 0.43 and overvalue Non-LEDs by 1.03 euros per bulb. The less informative signal increases the overvaluation for LEDs for both groups to around 1.80 per bulb. It also decreases consumers' undervaluation of Non-LEDs but leaves consumers with weaker environmental preferences with a larger bias of 2.32 euros per bulb (as opposed to 0.89 for green consumers). In terms of consumer surplus, households with lower green preferences benefit more from the fully informative signal and are hurt less by partial information disclosure than households with strong green preferences. The tax vector is similar to the scenario in which income is assumed to identify homogeneous subgroups but is characterized by both a slightly lower subsidy and a lower tax. Much of the tax burden is borne by green consumers who lose 5.94 euros per bulb per consumer, which is around 3.7 times more than non-green consumers. The reason for this asymmetry is again primarily attributable to the difference in own-price elasticities for Non-LED products.

6 Relation to Previous Studies

As pointed out in the literature review, several studies have analyzed whether subjects undervalue the monetary benefits from energy efficiency, generally with mixed results. Most related to our setting, Allcott and Taubinsky (2015) run two experiments in which they provide subjects with information about the monetary savings of CFLs relative to incandescent. One study is an experiment in a retail chain in which research assistants provide shop visitors with information about the monetary benefits of CFLs. This study finds no statistically significant effects of information provision. The other study is a survey experiment, in which respondents face a multiple price list with which they have to choose between a CFL and an incandescent bulb. Results suggest that information provision increases willingness-to-pay for CFLs and that subjects underestimate the expected savings from energy efficiency. Our results are in line with the finding that information about absolute savings of energy efficiency increases demand for CFLs but not with the notion that consumers undervalue energy efficiency. Based on these results, we would have expected an increase in demand for LEDs and in elicited savings beliefs.

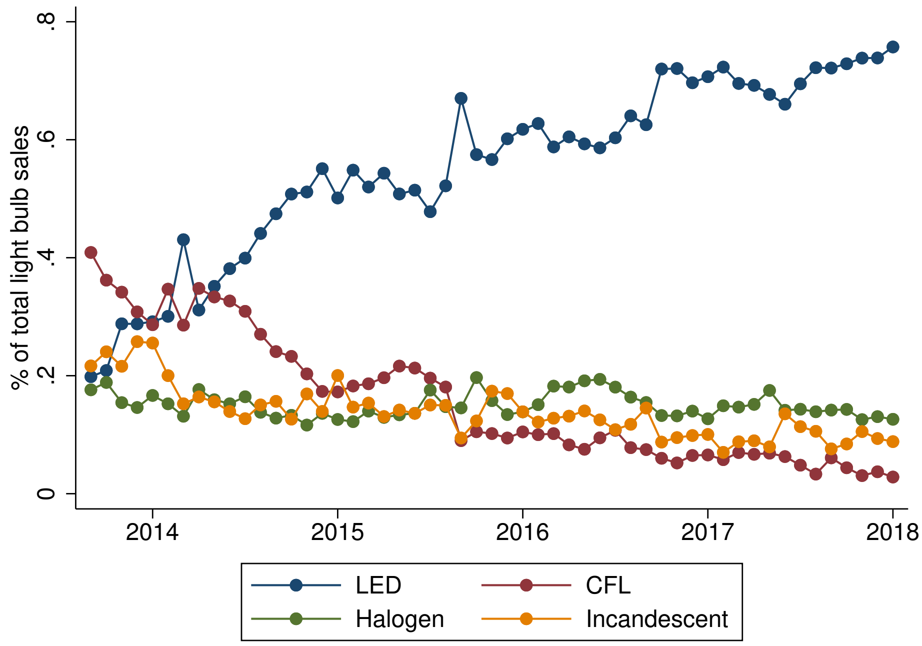
While it is not possible to identify the mechanisms that drive the lack of congruence, it is useful to compare observable differences between the two studies. First, the information in their survey experiment is framed over an eight-year lifetime of a CFL bulb. This framing effect might make energy savings appear larger than our treatment. It is generally unclear whether their lifetime framing or our annual framing is better at fully informing consumers. First evidence on these framing effects comes from a recent study in Italy by d'Adda, Gao, and Tavoni (2020) who find that framing energy costs of refrigerators over the lifetime rather than per year *decreases* rather than increases demand for energy efficiency. These results from another European country make us doubtful whether a different framing would reverse our results.

Second, the experiment by Allcott and Taubinsky (2015) was implemented at a different time (2013) than ours (2018) and with a sample from the US rather than from Germany. Differences in time matter, as in 2013 LED bulbs were mostly not available and the most efficient technology were CFLs. These bulbs were also notoriously disliked by consumers because they took more time to reach full brightness and included potentially harmful mercury content. By contrast, LED bulbs reach full brightness immediately and have no mercury content. Furthermore, it may still be that the average US consumer undervalues energy efficiency, while the opposite is true for German consumers.

To understand whether consumer behavior has changed since 2013, we requested historical transaction data from the company we ran the experiment with. The data include light bulb sales from the time of our experiment in 2018 back to the experiment by Allcott and Taubinsky (2015) in 2013. Figure 8 shows that over this time period, consumption behavior has substantially changed in the store. While in 2013, 40 percent of sold light bulbs were incandescent and halogen bulbs, in 2018 this number dropped to below 22 percent. The most dramatic change can be observed for CFLs and LEDs. The share of CFLs declined from 40 percent to only 3 percent, while the share of LED light bulbs increased from 20 percent to 76 percent.

This figure does not tell us how much of this change is driven by demand or supply, but it clearly shows a substantial shift in consumption behavior over the last years. Obviously, we cannot exclude the possibility that regional differences drive the lack of congruence with Allcott and Taubinsky (2015). However, we view this stark movement in the composition of technology purchases as suggestive evidence that the difference in treatment effects to the US study may be driven by differences over time rather than by differences in the sample of consumers.

Figure 8: Historical Composition of Light Bulb Sales



Note: The graph shows each technology's share in the company's monthly light bulb sales from September 2013 to January 2018. The field experiment was implemented in the summer of 2018.

7 Conclusion

How much information should governments provide to consumers if choices have uninternalized consequences to society? How do taxes compare to these informational interventions? We introduce a price theoretic model that incorporates choices under imperfect information and provides empirically estimable sufficient statistics to evaluate the welfare effects of any arbitrary information policy. We show that even information policies that shift multiple belief distributions simultaneously can be evaluated with knowledge of the Slutsky matrix and demand responses to the informational interventions. Policies that only partially inform consumers or even exacerbate informational frictions can be evaluated as long as the empiricist observes a counterfactual that is reasonably close to choices under full information. The model also allows for an apples-to-apples comparison between the efficiency effects of information and taxation. Real-world policies suggest that this trade-off is often made by governments, as many markets are regulated by only one of the two instruments.

We then take our model to the field and address a phenomena that is frequently attributed to informational frictions: consumers' allegedly low investment into energy efficiency. In cooperation with one of Europe's main appliance retailer for household lighting, we provide consumers with signals regarding the financial benefits of energy efficiency and systematically vary the informativeness of these signals. By randomizing prices and informativeness, we can identify the set of sufficient statistics produced by the theoretical model.

We find that full information disclosure drastically reduces demand for LED lighting by approximately 13 percent, suggesting that consumers overvalue energy efficiency of household lighting. By contrast, partial information disclosure further boosts demand for LEDs, thereby decreasing environmental externalities at the cost of increasing consumers' overvaluation even further. Movements in savings beliefs elicited in a follow-up survey are in line with these movements in demand: consumers overestimate savings in the control group, and this overestimation increases further with partial information disclosure. Full information disclosure shifts savings beliefs downwards and closer to true savings, even after correcting for heterogeneity.

Structural estimates suggest that in our experiment less information is better: partial information provision is more efficient than full information provision, and no information provision dominates both informational interventions. An alternative tax policy yields larger welfare gains than any of the implemented information policies and strongly increases welfare by correcting multiple market failures: externalities, markups, and informational frictions. Importantly, taxes need to be substantially larger when paired with information, as both informational treatments substantially crowd out attention to financial incentives.

Our study also lends itself to a comparison of the different information designs chosen by governments. While the EU energy efficiency label only provides a relative ranking of products into different classes of energy efficiency, the Energy Guide label in the US explicitly informs consumers about the average annual operating costs *and* provides a relative ranking of alternative products. If our treatment effects generalize to other samples, results of this study provide suggestive evidence that less informative labels may be preferred from a social welfare perspective.

Our methodological approach may be applied to any setting in which governments can use persuasion. Examples include information on high-caloric groceries, sugary beverages, cigarette packages, and fair-trade products among others. We hope that future research builds on our approach to evaluate the optimal information policy in these various markets.

References

Allcott, Hunt, and Christopher Knittel. 2019. "Are Consumers Poorly Informed About Fuel Economy? Evidence from Two Experiments." *American Economic Journal: Economic Policy* 11 (1): 1–37.

Allcott, Hunt, Christopher Knittel, and Dmitry Taubinsky. 2015. "Tagging and targeting of energy efficiency subsidies." *American Economic Review Papers and Precedings* 105 (5): 187–91.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky. 2019. "Regressive sin taxes, with an application to the optimal soda tax." *The 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* 112:72–88.

Allcott, Hunt, and Dmitry Taubinsky. 2015. "Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market." *The American Economic Review* 105 (8): 2501–2538.

Allcott, Hunt, and Nathan Wozny. 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics* 96 (5): 779–795.

Attari, Shahzeen Z., Michael L. DeKay, Cliff I. Davidson, and Wändi Bruine De Bruin. 2010. "Public Perceptions of Energy Consumption and Savings." *Proceedings of the National Academy of Sciences* 107 (37): 16054–16059.

Becker, Gary S., and Kevin M. Murphy. 1993. "A Simple Theory of Advertising As a Good or Bad." *The Quarterly Journal of Economics* 108 (4): 941–964.

Bernheim, B. Douglas, and Antonio Rangel. 2009. "Beyond Revealed Preference: Choice-Theoretic Foundations for Behavioral Welfare Economics." *The Quarterly Journal of Economics* 124 (1): 51–104.

Bernheim, B Douglas, and Dmitry Taubinsky. 2018. "Behavioral Public Economics." In *Handbook of Behavioral Economics: Applications and Foundations 1*, Volume 1, 381–516. Elsevier.

Blackwell, David. 1951. "Comparison of Experiments." *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability.* University of California Press, 93–102.

Chetty, Raj. 2009. "Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods." *Annual Review of Economics* 1 (1): 451–488.

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and Taxation: Theory and Evidence." *The American Economic Review* 99 (4): 1145–1177.

Coffman, Lucas, Clayton R. Featherstone, and Judd B. Kessler. 2015. "A Model of Information Nudges." Working paper.

d'Adda, Giovanna, Yu Gao, and Massimo Tavoni. 2020. "Making Energy Costs Salient Can Lead to Low-Efficiency Purchases." Working paper 045, E2e.

De Almeida, Anibal, Paula Fonseca, Barbara Schlomann, and Nicolai Feilberg. 2011. "Characterization of the Household Electricity Consumption in the EU, Potential Energy Savings and Specific Policy Recommendations." *Energy and Buildings* 43 (8): 1884–1894.

DellaVigna, Stefano. 2018. "Structural behavioral economics." In *Handbook of Behavioral Economics: Applications and Foundations 1*, Volume 1, 613–723. Elsevier.

DellaVigna, Stefano, and Matthew Gentzkow. 2010. "Persuasion: Empirical Evidence." *Annual Review of Economics* 2 (1): 643–669.

DellaVigna, Stefano, John A. List, and Ulrike Malmendier. 2012. "Testing for Altruism and Social Pressure in Charitable Giving." *The Quarterly Journal of Economics* 127 (1): 1–56 (February).

DellaVigna, Stefano, John A. List, Ulrike Malmendier, and Gautam Rao. 2016. "Voting to Tell Others." *The Review of Economic Studies* 84 (1): 143–181.

Enke, Benjamin, and Florian Zimmermann. 2019. "Correlation Neglect in Belief Formation." *The Review of Economic Studies* 86 (1): 313–332.

Falk, Armin, and Florian Zimmermann. 2018. "Information Processing and Commitment." *The Economic Journal* 128 (613): 1983–2002.

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

German Environment Agency. 2019. "Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990 - 2018." Technical Report 10/2019.

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.

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

Harrison, Glenn W, and John A List. 2004. "Field Experiments." *Journal of Economic Literature* 42 (4): 1009–1055.

Houde, Sébastien. 2017. “How Consumers Respond to Product Certification: A Welfare Analysis of the Energy Star Program.” *The RAND Journal of Economics.*

Houde, Sebastien, and Joseph E. Aldy. 2017. “The Efficiency Consequences of Heterogeneous Behavioral Responses to Energy Fiscal Policies.” Working paper 24103, National Bureau of Economic Research.

Jaffe, Adam B., and Robert N. Stavins. 1994. “The Energy-Efficiency Gap: What Does It Mean?” *Energy Policy* 22 (10): 804–810.

Kamenica, Emir, and Matthew Gentzkow. 2011. “Bayesian Persuasion.” *American Economic Review* 101 (6): 2590–2615.

Lacetera, Nicola, Devin G. Pope, and Justin R. Sydnor. 2012. “Heuristic Thinking and Limited Attention in the Car Market.” *American Economic Review* 102 (5): 2206–36.

Larrick, Richard P., and Jack B. Soll. 2008. “The MPG Illusion.” *Science* 320:1593–1594.

Milgrom, Paul R. 1981. “Good News and Bad News: Representation Theorems and Applications.” *The Bell Journal of Economics* 12 (2): 380–391.

Mullainathan, Sendhil, Joshua Schwartzstein, and William J. Congdon. 2012. “A Reduced-Form Approach to Behavioral Public Finance.” *Annual Review of Economics* 4 (1): 511–540.

New York Times. 2019. John Schwartz: White House to Relax Energy Efficiency Rules for Light Bulbs. URL: https://www.nytimes.com/2019/09/04/climate/trump-light-bulb-rollback.html (Retrieved: 04/09/2020).

Newell, Richard G., and Juha Siikamäki. 2014. “Nudging Energy Efficiency Behavior: The Role of Information Labels.” *Journal of the Association of Environmental and Resource Economists* 1 (4): 555–598.

Nordhaus, William D. 2018. “Climate Change: The Ultimate Challenge for Economics.” Nobel Lecture in Economic Sciences, Stockholm University.

O’Donoghue, Ted, and Matthew Rabin. 2006. “Optimal Sin Taxes.” *Journal of Public Economics* 90 (10): 1825–1849.

Taubinsky, Dmitry, and Alex Rees-Jones. 2017. “Attention Variation and Welfare: Theory and Evidence from a Tax Salience Experiment.” *The Review of Economic Studies* 85 (4): 2462–2496.

Zimmermann, Florian. 2020. “The Dynamics of Motivated Beliefs.” *American Economic Review* 110 (2): 337–61.

8 Online Appendix: Not for Publication

8.1 Proofs

Proof of Lemma 1

To show the relation between equilibrium demand responses and the misperception vector, we first derive the relevant comparative statics. The first-order condition for every i is $G^i := v_i - p_i - b_i(s_i) - \theta(\mathbf{s})t_i = 0$. Totally differentiating G^i yields

$$dG^i = \sum_{k=1}^{I} \frac{\partial v_i}{\partial x_k} dx_k - dp_i - \theta(\mathbf{s})dt_i - \left(\frac{\partial b_i(s_i)}{\partial s_i} + t_i \frac{\partial \theta(\mathbf{s})}{\partial s_i} \right) ds_i - \sum_{l \neq i} \frac{\partial \theta(\mathbf{s})}{\partial s_l} t_i ds_l.$$

To find the effect of a change in an exogenous variable $z_j \in \{p_j, t_j, s_j\}$ on x_i, set all changes in the other exogenous variables to zero except for dz_j, and divide dG^i by dz_j to get

$$\begin{aligned} \sum_{k=1}^{I} \frac{\partial G^i}{\partial x_k} \frac{dx_k}{dz_j} + \frac{\partial G^i}{\partial z_j} &= 0 \\ \Leftrightarrow \sum_{k=1}^{I} \frac{\partial v_i}{\partial x_k} \frac{dx_k}{dz_j} + \frac{\partial G^i}{\partial z_j} &= 0 \end{aligned}$$

for every i. In matrix notation this is

$$\begin{pmatrix} \frac{\partial v_1}{\partial x_1} & \cdots & \frac{\partial v_1}{\partial x_I} \\ \vdots & \ddots & \vdots \\ \frac{\partial v_I}{\partial x_1} & \cdots & \frac{\partial v_I}{\partial x_I} \end{pmatrix} \begin{pmatrix} \frac{dx_1}{dz_1} & \cdots & \frac{dx_1}{dz_I} \\ \vdots & \ddots & \vdots \\ \frac{dx_I}{dz_1} & \cdots & \frac{dx_I}{dz_I} \end{pmatrix} + \begin{pmatrix} \frac{\partial G^1}{\partial z_1} & \cdots & \frac{\partial G^1}{\partial z_I} \\ \vdots & \ddots & \vdots \\ \frac{\partial G^I}{\partial z_1} & \cdots & \frac{\partial G^I}{\partial z_I} \end{pmatrix} = \mathbf{0}$$

$$\Leftrightarrow \frac{\partial \mathbf{v}}{\partial \mathbf{x}} \frac{\mathbf{dx}}{\mathbf{dz}} = -\frac{\partial \mathbf{G}}{\partial \mathbf{z}},$$

where we use the notation $\frac{\partial \mathbf{v}}{\partial \mathbf{x}} := \frac{\partial v_j}{\partial x_k} \in \mathbb{R}^{I \times K}$, $\frac{\mathbf{dx}}{\mathbf{dz}} := \frac{dx_j}{dz_k} \in \mathbb{R}^{I \times K}$ and $\frac{\partial \mathbf{G}}{\partial \mathbf{z}} := \frac{\partial G^j}{\partial z_k} \in \mathbb{R}^{I \times K}$. By Cramer's rule,

$$\frac{dx_i}{dz_j} = -\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}(i,j)\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)},$$

where $\frac{\partial \mathbf{v}}{\partial \mathbf{x}}(i,j)$ is a matrix formed by replacing the i^{th} column of $\frac{\partial \mathbf{v}}{\partial \mathbf{x}}$ by the j^{th} column of $\frac{\partial \mathbf{G}}{\partial \mathbf{z}}$. By determinant expansion, we have

$$\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}(i,j)\right) = \sum_{k=1}^{I} \frac{\partial G^k}{\partial z_j} \det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{k,i}\right)(-1)^{i+k},$$

where $\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{k,i}$ denotes the matrix formed by deleting the k^{th} row and i^{th} column of $\frac{\partial \mathbf{v}}{\partial \mathbf{x}}$. Substituting this into the former expression gives

$$\frac{dx_i}{dz_j} = -\sum_{k=1}^{I}(-1)^{i+k}\frac{\partial G^k}{\partial p_j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{k,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \tag{22}$$

The derivative of demand for i with respect to the price of j is given by setting $dz_j = dp_j$ in equation 22:

$$\begin{aligned}\frac{dx_i}{dp_j} &= -\sum_{k=1}^{I}(-1)^{i+k}\frac{\partial G^k}{\partial p_j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{k,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \\ &= -(-1)^{i+j}\frac{\partial G^j}{\partial p_j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \\ &= (-1)^{i+j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)},\end{aligned}$$

where the second equality follows from the fact that $\frac{\partial G^k}{\partial p_j} = 0$ for all $k \neq j$.

Using equation 22, we can similarly derive the effects of a change in a policy instrument on demand for i. The effect of a change in the tax t_j by dt_j on demand for i is

$$\begin{aligned}\frac{dx_i}{dt_j} &= \theta(\mathbf{s})(-1)^{i+j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \\ &= \theta\frac{dx_i}{dp_j}.\end{aligned}$$

The effect of a change in s_j by ds_j is

$$\frac{dx_i}{ds_j} = -(-1)^{i+j}\left(-\frac{\partial b_j}{\partial s_j} - t_j\frac{\partial \theta}{\partial s_j}\right)\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} - \sum_{l\neq j}(-1)^{i+l}\left(-t_l\frac{\partial \theta}{\partial s_l}\right)\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{l,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)}.$$

If all taxes are zero, this simplifies to

$$\begin{aligned}\frac{dx_i(\mathbf{t}=\mathbf{0})}{ds_j} &= (-1)^{i+j}\left(\frac{\partial b_j}{\partial s_j}\right)\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \\ &= \frac{\partial b_j}{\partial s_j}\frac{dx_i}{dp_j}.\end{aligned}$$

We can therefore get a first-order approximation of the demand responses to $\mathbf{\Delta s}$ by

$$\Delta x_i(\mathbf{t}=0) \approx \Delta s_i \frac{\partial x_i}{\partial s_i} + \sum_{k\neq i} \Delta s_k \frac{\partial x_i}{\partial s_k} \tag{23}$$

$$= \Delta b_i \frac{dx_i}{dp_i} + \sum_{k\neq i} \Delta b_k \frac{dx_i}{dp_k} \tag{24}$$

for every i. In going from the first to the second line, we have used the previous result that, if taxes are zero, $\frac{dx_i(\mathbf{t}=\mathbf{0})}{ds_j} = \frac{\partial b_j}{\partial s_j}\frac{dx_i}{dp_j}$ and the first-order approximation $\Delta b_i \approx \frac{\partial b_i}{\partial s_i}\Delta s_i$. The system of linear equations given by equation 24 can be written in matrix notation as

$$\mathbf{\Delta x}' \approx \mathbf{\Delta b}'\mathbf{E}.$$

If the information policy is fully informative, this simplifies to

$$\mathbf{\Delta x}^{*\prime} = -\mathbf{b}'\mathbf{E}.$$

This completes the proof. □

Preliminaries

We first derive some results that are a useful technical support in the following proofs. Denote consumer surplus by $CS = u(\mathbf{x}(\mathbf{p},\mathbf{t},\mathbf{s}),\mathbf{p},\mathbf{t},\omega)$.

First-order derivatives of consumer surplus with respect to a policy tool are given by

$$\begin{aligned}\frac{\partial CS}{\partial t_i} &= (\theta(\mathbf{s})t_i + b_i(s_i))\frac{\partial x_i}{\partial t_i} + \sum_{j\neq i}(\theta(\mathbf{s})t_j + b_j(s_j))\frac{\partial x_j}{\partial t_i} \\ \frac{\partial CS}{\partial s_i} &= (\theta(\mathbf{s})t_i + b_i(s_i))\frac{\partial x_i}{\partial s_i} + \sum_{j\neq i}(\theta(\mathbf{s})t_j + b_j(s_j))\frac{\partial x_j}{\partial s_i}.\end{aligned}$$

Under the assumption that demand derivatives with respect to prices and signals are constant, second-order derivatives are given by

$$\frac{\partial^2 CS}{\partial t_i^2} = \theta(\mathbf{s})\frac{\partial x_i}{\partial t_i}$$
$$\frac{\partial^2 CS}{\partial s_i^2} = \left(\frac{\partial \theta(\mathbf{s})}{\partial s_i}t_i + \frac{\partial b_i}{\partial s_i}\right)\frac{\partial x_i}{\partial s_i} + \sum_j \frac{\partial \theta}{\partial s_i}t_j\frac{\partial x_j}{\partial s_i}.$$

Cross-partials are given by

$$\frac{\partial^2 CS}{\partial t_i \partial t_j} = \theta\frac{\partial x_j}{\partial t_i}$$
$$\frac{\partial^2 CS}{\partial s_i \partial s_j} = \frac{\partial \theta}{\partial s_j}t_i\frac{\partial x_i}{\partial s_i} + \left(\frac{\partial \theta}{\partial s_j}t_j + \frac{\partial b_j}{\partial s_j}\right)\frac{\partial x_j}{\partial s_i} + \sum_{k\neq i,j}\frac{\partial \theta}{\partial s_j}t_k\frac{\partial x_k}{\partial s_i}$$
$$\frac{\partial^2 CS}{\partial t_i \partial s_i} = \left(\frac{\partial \theta(\mathbf{s})}{\partial s_i}t_i + \frac{\partial b_i}{\partial s_i}\right)\frac{\partial x_i}{\partial t_i} + \sum_j \frac{\partial \theta}{\partial s_i}t_j\frac{\partial x_j}{\partial t_i}$$
$$\frac{\partial^2 CS}{\partial t_i \partial s_j} = \left(\frac{\partial \theta}{\partial s_j}t_i\right)\frac{\partial x_i}{\partial t_i} + \left(\frac{\partial \theta}{\partial s_j}t_j + \frac{\partial b_j}{\partial s_j}\right)\frac{\partial x_j}{\partial t_i} + \sum_{k\neq i,j}\frac{\partial \theta}{\partial s_j}t_k\frac{\partial x_k}{\partial t_i}$$
$$\frac{\partial^2 CS}{\partial s_i \partial t_i} = \theta(\mathbf{s})\frac{\partial x_i}{\partial s_i}$$
$$\frac{\partial^2 CS}{\partial s_i \partial t_j} = \theta(\mathbf{s})\frac{\partial x_j}{\partial s_i}.$$

Proof of Proposition 1

The effect of changing ρ by $\mathbf{\Delta}\rho$ on consumer surplus is

$$CS(\rho + \mathbf{\Delta}\rho) - CS(\rho) \approx \mathbf{\Delta}\rho'\nabla CS + \frac{1}{2}\left(\mathbf{\Delta}\rho'\mathbf{H}\mathbf{\Delta}\rho\right), \tag{25}$$

with $\mathbf{H}$ being the Hessian of CS.

We consider a situation with no previous taxes and no previous informational interventions such that $t_i = s_i = 0$ for all i and therefore also $\theta(\mathbf{0}) = 1$.

The first-order effect on consumer surplus is

$$\mathbf{\Delta}\rho'\nabla CS = \left(\begin{array}{c} \mathbf{\Delta t}, \mathbf{\Delta s} \end{array} \right)' \begin{pmatrix} b_1 \frac{\partial x_1}{\partial t_1} + \sum_{j \neq 1} b_j \frac{\partial x_j}{\partial t_1} \\ \vdots \\ b_I \frac{\partial x_I}{\partial t_I} + \sum_{j \neq I} b_j \frac{\partial x_j}{\partial t_I} \\ b_1 \frac{\partial x_1}{\partial s_1} + \sum_{j \neq 1} b_j \frac{\partial x_j}{\partial s_1} \\ \vdots \\ b_I \frac{\partial x_I}{\partial s_I} + \sum_{j \neq I} b_j \frac{\partial x_j}{\partial s_I} \end{pmatrix}$$

$$= \left(\begin{array}{c} \mathbf{\Delta t}, \mathbf{\Delta s} \end{array} \right)' \begin{pmatrix} \frac{\partial x_1}{\partial t_1} & \cdots & \frac{\partial x_I}{\partial t_1} \\ \vdots & \ddots & \\ \frac{\partial x_1}{\partial t_I} & \cdots & \frac{\partial x_I}{\partial t_I} \\ \frac{\partial x_1}{\partial s_1} & \cdots & \frac{\partial x_I}{\partial s_1} \\ \vdots & \ddots & \\ \frac{\partial x_1}{\partial s_I} & \cdots & \frac{\partial x_I}{\partial s_I} \end{pmatrix} \mathbf{b}$$

$$= \left(\begin{array}{c} \mathbf{\Delta t}, \mathbf{\Delta b} \end{array} \right)' \begin{pmatrix} \frac{\partial x_i}{\partial t_i} & \cdots & \frac{\partial x_I}{\partial t_i} \\ \vdots & & \\ \frac{\partial x_i}{\partial t_I} & \cdots & \frac{\partial x_I}{\partial t_I} \\ \frac{\partial x_i}{\partial p_i} & \cdots & \frac{\partial x_I}{\partial p_i} \\ \vdots & & \\ \frac{\partial x_i}{\partial p_I} & \cdots & \frac{\partial x_I}{\partial p_I} \end{pmatrix} \mathbf{b}$$

$$= \left(\begin{array}{c} \mathbf{\Delta t} + \mathbf{\Delta b} \end{array} \right)' \begin{pmatrix} \frac{\partial x_i}{\partial p_i} & \cdots & \frac{\partial x_I}{\partial p_i} \\ \vdots & & \\ \frac{\partial x_i}{\partial p_I} & \cdots & \frac{\partial x_I}{\partial p_I} \end{pmatrix} \mathbf{b}$$

$$= (\mathbf{\Delta t}'\mathbf{E} + \mathbf{\Delta b}'\mathbf{E})\mathbf{b}$$

$$= -(\mathbf{\Delta t}'\mathbf{E} + \mathbf{\Delta x}')\mathbf{E}^{-\mathbf{1}}\mathbf{\Delta x}^*,$$

where we have used the results from Lemma 1.

The second-order effect on consumer surplus is

$$
\begin{aligned}
\frac{1}{2}\boldsymbol{\Delta}\rho'\mathbf{H}\boldsymbol{\Delta}\rho &= \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{s})'
\begin{pmatrix}
\frac{\partial^2 CS}{\partial t_1^2} & \cdots & \frac{\partial^2 CS}{\partial t_1 \partial t_I} & \frac{\partial^2 CS}{\partial t_1 \partial s_1} & \cdots & \frac{\partial^2 CS}{\partial t_1 \partial s_I} \\
\vdots & \ddots & & & & \vdots \\
\frac{\partial^2 CS}{\partial t_I \partial t_1} & \cdots & \frac{\partial^2 CS}{\partial t_I^2} & \frac{\partial^2 CS}{\partial t_I \partial s_1} & \cdots & \frac{\partial^2 CS}{\partial t_I \partial s_I} \\
\frac{\partial^2 CS}{\partial s_1 \partial t_1} & \cdots & \frac{\partial^2 CS}{\partial s_1 \partial t_I} & \frac{\partial^2 CS}{\partial s_1^2} & \cdots & \frac{\partial^2 CS}{\partial s_1 \partial s_I} \\
\vdots & & & & \ddots & \vdots \\
\frac{\partial^2 CS}{\partial s_I \partial t_1} & \cdots & \frac{\partial^2 CS}{\partial s_I \partial t_I} & \frac{\partial^2 CS}{\partial s_I \partial s_1} & \cdots & \frac{\partial^2 CS}{\partial s_I^2}
\end{pmatrix}
(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{s}) \\
&= \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{s})'
\begin{pmatrix}
\frac{\partial x_1}{\partial t_1} & \cdots & \frac{\partial x_I}{\partial t_1} & \frac{\partial b_1}{\partial s_1}\frac{\partial x_1}{\partial t_1} & \cdots & \frac{\partial b_I}{\partial s_I}\frac{\partial x_I}{\partial t_1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
\frac{\partial x_1}{\partial t_I} & \cdots & \frac{\partial x_I}{\partial t_I} & \frac{\partial b_1}{\partial s_1}\frac{\partial x_1}{\partial t_I} & \cdots & \frac{\partial b_I}{\partial s_I}\frac{\partial x_I}{\partial t_I} \\
\frac{\partial x_1}{\partial s_1} & \cdots & \frac{\partial x_I}{\partial s_1} & \frac{\partial b_1}{\partial s_1}\frac{\partial x_1}{\partial s_1} & \cdots & \frac{\partial b_I}{\partial s_I}\frac{\partial x_I}{\partial s_1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
\frac{\partial x_1}{\partial s_I} & \cdots & \frac{\partial x_I}{\partial s_I} & \frac{\partial b_1}{\partial s_1}\frac{\partial x_1}{\partial s_I} & \cdots & \frac{\partial b_I}{\partial s_I}\frac{\partial x_I}{\partial s_I}
\end{pmatrix}
(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{s}) \\
&= \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{b})'
\begin{pmatrix}
\frac{\partial x_1}{\partial t_1} & \cdots & \frac{\partial x_I}{\partial t_1} & \frac{\partial x_1}{\partial t_1} & \cdots & \frac{\partial x_I}{\partial t_1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
\frac{\partial x_1}{\partial t_I} & \cdots & \frac{\partial x_I}{\partial t_I} & \frac{\partial x_1}{\partial t_I} & \cdots & \frac{\partial x_I}{\partial t_I} \\
\frac{\partial x_1}{\partial p_1} & \cdots & \frac{\partial x_I}{\partial p_1} & \frac{\partial x_1}{\partial p_1} & \cdots & \frac{\partial x_I}{\partial p_1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
\frac{\partial x_1}{\partial p_I} & \cdots & \frac{\partial x_I}{\partial p_I} & \frac{\partial x_1}{\partial p_I} & \cdots & \frac{\partial x_I}{\partial p_I}
\end{pmatrix}
(\boldsymbol{\Delta}\mathbf{t},\boldsymbol{\Delta}\mathbf{b}) \\
&= \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t}+\boldsymbol{\Delta}\mathbf{b})'\mathbf{E}(\boldsymbol{\Delta}\mathbf{t}+\boldsymbol{\Delta}\mathbf{b}) \\
&= \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}+\boldsymbol{\Delta}\mathbf{x}')(\boldsymbol{\Delta}\mathbf{t}+\mathbf{E}^{-1}\boldsymbol{\Delta}\mathbf{x}).
\end{aligned}
$$

Putting both first- and second-order terms together, we have

$$
\begin{aligned}
\Delta CS &\approx -(\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}+\boldsymbol{\Delta}\mathbf{x}')(\mathbf{E}^{-1}\boldsymbol{\Delta}\mathbf{x}^*) + \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}+\boldsymbol{\Delta}\mathbf{x}')(\boldsymbol{\Delta}\mathbf{t}+\mathbf{E}^{-1}\boldsymbol{\Delta}\mathbf{x}) \\
&= (\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}+\boldsymbol{\Delta}\mathbf{x}')\left(\frac{1}{2}\boldsymbol{\Delta}\mathbf{t}+\mathbf{E}^{-1}(\frac{1}{2}\boldsymbol{\Delta}\mathbf{x}-\boldsymbol{\Delta}\mathbf{x}^*)\right).
\end{aligned}
$$

Adding the linear effects on firm profits and externalities yields the effect on social welfare:

$$
\Delta W \approx (\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}+\boldsymbol{\Delta}\mathbf{x}')\left(\frac{1}{2}\boldsymbol{\Delta}\mathbf{t}+\mathbf{E}^{-1}(\frac{1}{2}\boldsymbol{\Delta}\mathbf{x}-\boldsymbol{\Delta}\mathbf{x}^*)+(\mathbf{m}-\epsilon)\right),
$$

which is the first part of the statement in the proposition. The optimal tax vector is obtained by setting $\nabla W = \mathbf{0}$:

$$\nabla W = \begin{pmatrix} (\theta(\mathbf{s})t_1 + b_1 + m_1 - \epsilon_1)\frac{\partial x_1}{\partial t_1} + \sum_{j\neq 1}(\theta(\mathbf{s})t_j + b_j + m_j - \epsilon_j)\frac{\partial x_j}{\partial t_1} \\ \vdots \\ (\theta(\mathbf{s})t_I + b_I + m_i - \epsilon_I)\frac{\partial x_I}{\partial t_I} + \sum_{j\neq I}(\theta(\mathbf{s})t_j + b_j + m_j - \epsilon_j)\frac{\partial x_j}{\partial t_I} \\ (\theta(\mathbf{s})t_1 + b_1 + m_1 - \epsilon_1)\frac{\partial x_1}{\partial s_1} + \sum_{j\neq 1}(\theta(\mathbf{s})t_j + b_j + m_j - \epsilon_j)\frac{\partial x_j}{\partial s_1} \\ \vdots \\ (\theta(\mathbf{s})t_I + b_I + m_i - \epsilon_I)\frac{\partial x_I}{\partial s_I} + \sum_{j\neq I}(\theta(\mathbf{s})t_j + b_j + m_j - \epsilon_j) \end{pmatrix} = \mathbf{0}, \tag{26}$$

which is fulfilled when each tax corrects the frictions in its respective market. Since consumers may not be fully attentive to taxes, frictions need to be scaled by the tax-inattention parameter. Formally, a solution to equation 26 is given by $t_i^* = (-b_i(s_i) - m_i + \epsilon_i)\,\theta(\mathbf{s})^{-1}$ for all i. In vector notation this is $\mathbf{t}^* = (-\mathbf{b}(\mathbf{s}) - \mathbf{m} + \epsilon)\theta(\mathbf{s})^{-1}$. Using Lemma 1, we can rewrite this as

$$\mathbf{t}^* = \left(E^{-1}\boldsymbol{\Delta}\mathbf{x}^*(\mathbf{s}) + m - \epsilon\right)\theta(\mathbf{s})^{-1},$$

which is the second part of the statement in the proposition. This completes the proof. □

Proof of Corollary 1

Follows immediately from Proposition 1 by setting $\boldsymbol{\Delta}\mathbf{t} = \mathbf{0}$. □

Proof of Corollary 2

Follows immediately from Proposition 1 by setting $\boldsymbol{\Delta}\mathbf{s} = \mathbf{0}$. □

Proof of Proposition 2

The effect on consumer surplus under heterogeneity in $\mathbf{b}$ and $\boldsymbol{\Delta}\mathbf{b}$ is simply the expectation of the individual effects, where the expectation, is taken over the conditional distribution function H. We let the subscript in the expectation operator indicate the distribution over which the expectation is taken. The effect on consumer surplus conditional on a state of the world can then be written as:

$$\begin{aligned}\Delta CS &\approx \mathbb{E}_H\left[(\boldsymbol{\Delta}\mathbf{t}'\mathbf{E} + \boldsymbol{\Delta}\mathbf{b}'\mathbf{E})\left(\mathbf{b} + \frac{1}{2}(\boldsymbol{\Delta}\mathbf{t} + \boldsymbol{\Delta}\mathbf{b})\right)\right] \\ &= \underbrace{\mathbb{E}_H\left[\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}\left(\mathbf{b} + \frac{\boldsymbol{\Delta}\mathbf{t}}{2}\right)\right]}_{\text{Effect of tax in isolation}} + \underbrace{\mathbb{E}_H\left[\boldsymbol{\Delta}\mathbf{b}'\mathbf{E}(\mathbf{b} + \frac{1}{2}\boldsymbol{\Delta}\mathbf{b})\right]}_{\text{Effect of information in isolation}} + \underbrace{\mathbb{E}_H\left[\boldsymbol{\Delta}\mathbf{t}'\mathbf{E}\boldsymbol{\Delta}\mathbf{b}\right]}_{\text{Interaction effect of policies}}.\end{aligned}$$

We can see that

$$
\begin{aligned}
\mathbb{E}_H\left[\mathbf{\Delta b'Eb}\right] &= -\mathbb{E}_H\left[\mathbf{\Delta x'E^{-1}\Delta x^*}\right] \\
&= -\mathbb{E}_H\left[\sum_i \sum_j \tilde{e}_{ij}[\Delta x_i \Delta x_j^*]\right] \\
&= -\sum_i \sum_j \tilde{e}_{ij}\mathbb{E}_H[\Delta x_i \Delta x_j^*] \\
&= -\sum_i \sum_j \tilde{e}_{ij}\left(\mathbb{E}_H[\Delta x_i]\mathbb{E}_H[\Delta x_j^*] + cov(\Delta x_i, \Delta x_j^*|\omega)\right) \\
&= -\mathbb{E}_H[\mathbf{\Delta x'}]\mathbf{E}\mathbb{E}_H[\mathbf{\Delta x^*}] + \sum_j \sum_i \frac{det(\mathbf{E}(i,j))}{det(\mathbf{E})} cov(\Delta x_i, \Delta x_j^*|\omega),
\end{aligned}
$$

where $\tilde{e}_{ij}$ is the entry in the i^{th} row and j^{th} column of the inverse of the Slutsky matrix, $\mathbf{E}^{-1}$. $\mathbf{E}(i,j)$ is a matrix formed by replacing the i^{th} column of $\mathbf{E}$ by the j^{th} column of the identity matrix of $\mathbf{E}$.

Furthermore, we have

$$
\begin{aligned}
\mathbb{E}_H[\mathbf{\Delta b'E\Delta b}] &= \mathbb{E}_H[\mathbf{\Delta b'}]\mathbf{E}\mathbb{E}_H[\mathbf{\Delta b}] + Tr[\mathbf{E}\Sigma_{\mathbf{\Delta b},\omega}] \\
&= \mathbb{E}_H[\mathbf{\Delta x'}]\mathbf{E}^{-1}\mathbb{E}_H[\mathbf{\Delta x}] + Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x},\omega}],
\end{aligned}
$$

where we use $Tr[\mathbf{E}\Sigma_{\mathbf{\Delta b},\omega}] = Tr[\mathbf{E}\times cov(\mathbf{E^{-1}\Delta x})] = Tr[\mathbf{E}\times\mathbf{E^{-1}}cov(\mathbf{\Delta x}|\omega)\mathbf{E}^{-1}] = Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x},\omega}]$.

We can therefore rewrite the effect on consumer surplus as

$$
\begin{aligned}
CS \approx\ & \mathbb{E}_H\left[\mathbf{\Delta t'E}\left(\frac{\mathbf{\Delta t}}{2} - \mathbf{E}^{-1}\mathbf{\Delta x^*}\right)\right] - \mathbb{E}_H[\mathbf{\Delta x'}]\mathbf{E}^{-1}\mathbb{E}_H[\mathbf{\Delta x^*}] + \sum_j \sum_i \frac{det(\mathbf{E}(i,j))}{det(\mathbf{E})} cov(\Delta x_i, \Delta x_j^*|\omega) \\
&+ \frac{1}{2}\left(\mathbb{E}_H[\mathbf{\Delta x'}]\mathbf{E}^{-1}\mathbb{E}_H[\mathbf{\Delta x}] + Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x},\omega}]\right) + \mathbb{E}_H\left[\mathbf{\Delta t'\Delta x}\right] \\
&= \Delta\mathbf{t'E}\left(\frac{1}{2}\mathbf{\Delta t} + \mathbf{E}^{-1}\left(\frac{1}{2}\mathbb{E}_H[\mathbf{\Delta x}] - \mathbb{E}_H[\mathbf{\Delta x^*}]\right)\right) + \mathbb{E}_H[\mathbf{\Delta x'}]\left(\frac{1}{2}\mathbf{\Delta t} + \mathbf{E}^{-1}\left(\frac{1}{2}\mathbb{E}_H[\mathbf{\Delta x}] - \mathbb{E}_H[\mathbf{\Delta x^*}]\right)\right) \\
&+ \sum_j \sum_i \frac{det(\mathbf{E}(i,j))}{det(\mathbf{E})} cov(\Delta x_i, \Delta x_j^*|\omega) + \frac{1}{2}Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x}}, \omega] \\
&= (\mathbf{\Delta t'E} + \mathbb{E}_H[\mathbf{\Delta x'}])\left(\frac{1}{2}\mathbf{\Delta t} + \mathbf{E}^{-1}\left(\frac{1}{2}\mathbb{E}_H[\mathbf{\Delta x}] - \mathbb{E}_H[\mathbf{\Delta x^*}]\right)\right) + \sum_j \sum_i \frac{det(\mathbf{E}(i,j))}{det(\mathbf{E})} \\
& cov(\Delta x_i, \Delta x_j^*|\omega) + \frac{1}{2}Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x},\omega}].
\end{aligned}
$$

Adding the effect on markups and externalities yields the welfare effect stated in Proposition 2.

Since the only source of heterogeneity are informational frictions, the optimal tax vector under heterogeneity, denoted $\mathbf{t}^*_{\mathbf{mh}}$, simply corrects the expected information frictions and the (deterministic) markups and externalities:

$$\mathbf{t}^*_{mh} = \left(\mathbf{E}^{-1}\mathbb{E}_H[\mathbf{\Delta x}^*] + \mathbf{m} - \epsilon\right)\theta(\mathbf{s})^{-1}.$$

This completes the proof. $\square$

Proof of Corollary 3

A fully informative signal has $\mathbf{\Delta b} = \mathbf{0} - \mathbf{b}$ such that the effect on consumer surplus is

$$\begin{aligned}
&\mathbb{E}_H\left[\mathbf{\Delta b}'\mathbf{E}(\mathbf{b} + \frac{1}{2}\mathbf{\Delta b})\right] \\
&= -\frac{1}{2}\mathbb{E}_H\left[\mathbf{b}'\mathbf{E}\mathbf{b}\right] \\
&= -\frac{1}{2}\mathbb{E}_H\left[(\mathbf{\Delta x}^*)'\mathbf{E}^{\mathbf{-1}}\mathbf{\Delta x}^*\right] \\
&= -\frac{1}{2}\left(\mathbb{E}_H[(\mathbf{\Delta x}^*)']\mathbf{E}^{-1}\mathbb{E}_H[\mathbf{\Delta x}^*] + Tr[\mathbf{E}^{-1}\Sigma_{\mathbf{\Delta x}^*,\omega}]\right)
\end{aligned}$$

since $\mathbf{E}$ is negative definite, $\mathbf{E}\Sigma_{\mathbf{\Delta b},\omega}$ is semi negative definite, and its trace is weakly negative. It follows that the welfare effect is larger when misperceptions are heterogeneous because the trace becomes strictly negative. This completes the proof. $\square$

8.2 Additional Tables

Table A1: Summary Table

Variable	More informative (M)	Less informative (L)	Control (C)	M & LED	L & LED	C & LED	M & CFL	L & CFL	C & CFL	M & Halogen	L & Halogen	C & Halogen	M & Incandescent	L & Incandescent	C & Incandescent
Sessions	1.865	1.857	1.860	1.859	1.864	1.861	1.862	1.852	1.870	1.861	1.870	1.856	1.862	1.871	1.865
	(2.352)	(2.194)	(2.318)	(2.559)	(2.404)	(2.280)	(2.296)	(2.194)	(2.426)	(2.449)	(2.489)	(2.378)	(2.341)	(2.470)	(2.380)
Purchase (Yes = 1)	0.044	0.045	0.045	0.045	0.045	0.046	0.045	0.045	0.046	0.046	0.046	0.046	0.043	0.045	0.045
	(0.205)	(0.206)	(0.207)	(0.206)	(0.208)	(0.209)	(0.207)	(0.206)	(0.209)	(0.209)	(0.209)	(0.208)	(0.204)	(0.207)	(0.207)
LED	0.541	0.533	0.514	0.546	0.591	0.667	0.531	0.590	0.618	0.543	0.618	0.518	0.549	0.492	0.554
	(2.720)	(1.810)	(1.845)	(1.898)	(2.334)	(2.432)	(1.958)	(2.166)	(2.285)	(3.538)	(2.894)	(2.346)	(3.319)	(2.221)	(2.034)
CFL	0.033	0.013	0.015	0.011	0.011	0.029	0.031	0.014	0.018	0.013	0.018	0.014	0.026	0.017	0.022
	(0.466)	(0.233)	(0.289)	(0.237)	(0.165)	(0.701)	(0.835)	(0.212)	(0.334)	(0.271)	(0.391)	(0.234)	(0.421)	(0.337)	(0.584)
Halogen	0.145	0.122	0.101	0.095	0.093	0.084	0.149	0.086	0.127	0.110	0.118	0.129	0.124	0.154	0.129
	(1.294)	(1.180)	(0.817)	(0.869)	(0.697)	(0.695)	(1.329)	(0.925)	(1.018)	(1.268)	(0.995)	(0.845)	(0.955)	(1.517)	(1.329)
Incandescent	0.070	0.039	0.086	0.036	0.180	0.125	0.041	0.077	0.156	0.082	0.074	0.065	0.088	0.051	0.128
	(1.157)	(0.593)	(1.626)	(0.851)	(3.426)	(2.658)	(0.712)	(1.336)	(2.600)	(2.004)	(1.389)	(0.873)	(1.417)	(0.946)	(2.425)
Shipping time (in workdays)	1.064	1.049	1.047	1.045	1.048	1.053	1.053	1.054	1.047	1.045	1.048	1.049	1.050	1.046	1.051
	(0.351)	(0.270)	(0.265)	(0.273)	(0.291)	(0.295)	(0.272)	(0.296)	(0.279)	(0.277)	(0.277)	(0.294)	(0.283)	(0.280)	(0.292)
Pre-paid (Yes = 1)	77.808	78.683	79.884	80.087	76.100	77.837	77.543	80.086	76.670	77.848	78.140	76.709	78.476	78.711	77.280
	(41.565)	(40.966)	(40.097)	(39.946)	(42.659)	(41.546)	(41.741)	(39.946)	(42.304)	(41.538)	(41.341)	(42.280)	(41.110)	(40.946)	(41.914)
No invoice in package (Yes = 1)	0.153	0.139	0.163	0.139	0.137	0.138	0.148	0.161	0.153	0.160	0.149	0.143	0.146	0.135	0.147
	(0.360)	(0.346)	(0.369)	(0.346)	(0.344)	(0.345)	(0.355)	(0.368)	(0.360)	(0.367)	(0.356)	(0.350)	(0.354)	(0.342)	(0.354)
Observations	42,955	42,844	43,257	42,621	42,824	42,530	42,529	42,829	43,043	42,564	42,787	42,686	42,706	42,215	42,634

Note: This table presents the mean of observable variables in different treatment conditions. To economize on space, "M," "L," and "C" indicate experimental groups that received the more informative signal, less informative signal, or no information (control), respectively. Standard deviations are reported in parentheses.

Table A2: Average Treatment Effects on Purchase Probability — All Interactions Included

	(1)
More informative	–0.0013
	(0.0014)
Less informative	–0.0003
	(0.0014)
LED	0.0007
	(0.0014)
CFL	0.0007
	(0.0014)
Halogen	0.0003
	(0.0014)
Incandescent	–0.0004
	(0.0014)
More informative & LED	–0.0004
	(0.0014)
More informative & CFL	–0.0002
	(0.0014)
More informative & Halogen	0.0009
	(0.0014)
More informative & Incandescent	–0.0016
	(0.0014)
Less informative & LED	0.0003
	(0.0014)
Less informative & CFL	–0.0005
	(0.0014)
Less informative & Halogen	0.0006
	(0.0014)
Less informative & Incandescent	–0.0000
	(0.0014)
Observations	640,771
Baseline probability	0.0446

Note: The table shows average marginal effects from a probit of 1(Purchase) on each of the 14 treatments. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A3: Average Treatment Effects on Demand – All Interactions Included

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.027	0.033**	–0.006	0.004
	(0.054)	(0.013)	(0.021)	(0.012)
Less informative	0.101*	0.007	–0.008	0.024
	(0.056)	(0.008)	(0.023)	(0.014)
Price discounts:				
LED	0.179***	0.001	0.003	0.016
	(0.059)	(0.009)	(0.025)	(0.014)
CFL	0.096*	0.010	0.009	0.036**
	(0.054)	(0.009)	(0.023)	(0.017)
Halogen	0.002	0.004	0.028	0.012
	(0.051)	(0.007)	(0.021)	(0.015)
Incandescent	0.056	0.005	0.006	0.018
	(0.052)	(0.006)	(0.022)	(0.013)
Interactions:				
More informative & LED	0.087	0.010	–0.007	0.006
	(0.055)	(0.009)	(0.023)	(0.014)
More informative & CFL	0.040	0.005	0.033	0.003
	(0.054)	(0.010)	(0.024)	(0.012)
More informative & Halogen	–0.053	0.010	–0.008	0.013
	(0.052)	(0.008)	(0.022)	(0.013)
More informative & Incandescent	–0.002	0.014	0.016	–0.000
	(0.055)	(0.010)	(0.025)	(0.016)
Less informative & LED	0.097*	0.002	0.008	0.007
	(0.055)	(0.007)	(0.025)	(0.012)
Less informative & CFL	0.056	0.010	–0.026	–0.001
	(0.056)	(0.008)	(0.021)	(0.011)
Less informative & Halogen	0.009	0.003	0.011	0.008
	(0.054)	(0.008)	(0.023)	(0.014)
Less informative & Incandescent	–0.009	0.004	–0.004	0.002
	(0.051)	(0.012)	(0.023)	(0.012)
Control group mean	0.428	0.011	0.079	0.019
N	28,553	28,553	28,553	28,553

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on each of the 14 treatments. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A4: Average Treatment Effects on Demand – All Purchases

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.042*	0.007	–0.012	–0.011*
	(0.025)	(0.005)	(0.011)	(0.007)
Less informative	–0.008	0.000	–0.012	–0.008
	(0.025)	(0.004)	(0.011)	(0.006)
Price discounts:				
LED	0.117***	–0.007	0.010	0.000
	(0.033)	(0.006)	(0.014)	(0.007)
CFL	0.054	–0.005	0.018	0.005
	(0.033)	(0.007)	(0.014)	(0.008)
Halogen	–0.038	–0.009	0.018	0.001
	(0.031)	(0.006)	(0.013)	(0.008)
Incandescent	0.012	–0.006	0.019	–0.003
	(0.032)	(0.007)	(0.014)	(0.007)
Control group mean	0.435	0.011	0.077	0.017
N	31,134	31,134	31,134	31,134

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on pooled treatments. First and all subsequent purchases of a subject are included. Standard errors clustered on individual level. Day and zip code fixed effects are included. Robust standard errors are in parentheses.*,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A5: Average Treatment Effects – All Non-LEDs Pooled into one Category – Treatments Pooled

	(1) LED (most energy efficient)	(2) Non-LED
Information treatments:		
More informative	–0.058**	–0.005
	(0.025)	(0.014)
Less informative	–0.015	–0.020
	(0.025)	(0.013)
Price discounts:		
LED	0.096***	–0.003
	(0.033)	(0.018)
Inefficient	–0.003	0.007
	(0.026)	(0.014)
Control group mean	0.428	0.109
N	28,553	28,553

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on pooled treatments. All non-LED technologies are pooled into one category to increase statistical power. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A6: Average Treatment Effects – All Non-LEDs pooled into one Category – All Interactions Included

	(1) LED (most energy efficient)	(2) Non-LED
Information treatments:		
More informative	–0.026	0.031
	(0.054)	(0.029)
Less informative	0.102*	0.022
	(0.056)	(0.028)
Price discounts:		
More informative & LED	0.086	0.009
	(0.055)	(0.028)
Less informative & LED	0.097*	0.018
	(0.055)	(0.030)
More informative & Inefficient	–0.006	0.029
	(0.044)	(0.023)
Less informative & Inefficient	0.019	0.003
	(0.044)	(0.022)
LED	0.179***	0.019
	(0.059)	(0.030)
Inefficient	0.051	0.043*
	(0.043)	(0.022)
Control group mean	0.428	0.109
N	28,553	28,553

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on all treatments. All non-LED technologies are pooled into one category to increase statistical power. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Structural Estimations with Heterogeneity in Income

Table A7: Structural Estimates – Only Subjects with Nonmissing Income Data

	LED	Non-LED
Demand slopes (dx/dp):		
LED	–0.112***	–0.016
	(0.021)	(0.013)
Inefficient	–0.016	–0.068**
	(0.013)	(0.029)
Demand responses to information (Δx):		
More informative	–0.073*	0.065***
	(0.040)	(0.024)
Less informative	0.118***	0.030
	(0.040)	(0.024)
Tax salience with information (θ_z):		
θ_m	0.584***	
	(0.182)	
θ_l	0.367**	
	0.184	
N	21,942	
Misperception (in €per light bulb):		
b_{LED}	–0.81	
$b_{non-LED}$	1.14	
Misperception after provision of less informative signal:		
b_{LED}	–1.83	
$b_{non-LED}$	0.94	

Note: Only subjects from zip codes with available data on average income are included. Estimation techniques and calculations are the same as in Table 4. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A8: Welfare Estimates Assuming Homogeneity – Only Subjects with Nonmissing Income Data

Policy	Δ Utility (€/consumer)	Δ Profits (€/consumer)	Δ Externalities (€/consumer)	Δ Welfare (€/consumer)
More informative signal	0.07	0.19	1.12	–0.86
Less informative signal	–0.12	0.61	0.72	–0.23
Optimal tax: t_{led} = –1.29 €/bulb, t_{Inef} = 1.79 €/bulb	–4.62	–4.89	–13.32	3.82

Note: Only subjects from zip codes with available data on average income are included.

Structural Estimations with Heterogeneity in Green Party Support

Table A9: Structural Estimates – Only Subjects from Zip Codes with Available Data on Political Votes

	LED	Non-LED
Demand slopes (dx/dp):		
LED	–0.119***	–0.016
	(0.021)	(0.013)
Inefficient	–0.016	–0.071**
	(0.013)	(0.029)
Demand responses to information (Δx):		
More informative	–0.071*	0.067***
	(0.040)	(0.024)
Less informative	0.122***	0.026
	(0.040)	(0.024)
Tax salience with information (θ_z):		
θ_m	0.557***	
	(0.175)	
θ_l	0.362**	
	0.177	
N	21,467	
Misperception (in €per lightbulb):		
b_{LED}	–0.75	
$b_{non-LED}$	1.13	
Misperception after provision of less informative signal:		
b_{LED}	–1.76	
$b_{non-LED}$	0.99	

Note: Only subjects from zip codes with available data on political votes are included. Estimation techniques and calculations are the same as in Table 4. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A10: Welfare Estimates Assuming Homogeneity – Only Subjects from Zip Codes with Available Data on Political Votes Included

Policy	Δ Utility (€/consumer)	Δ Profits (€/consumer)	Δ Externalities (€/consumer)	Δ Welfare (€/consumer)
More informative signal	0.06	0.21	1.16	–0.89
Less informative signal	–0.13	0.59	0.65	–0.18
Optimal tax: t_{led} = -1.35 €/bulb, t_{Inef} = 1.80 €/bulb	–4.79	–5.03	–13.79	3.97

Table A11: Structural Estimates: Heterogeneity in Green Party Support

	Non-green consumers		Green consumers	
	LED	Non-LED	LED	Non-LED
Demand slopes (dx/dp):				
LED	–0.135***	–0.024	–0.110***	–0.011
	(0.031)	(0.015)	(0.029)	(0.020)
Non-LED	–0.024	–0.025	–0.011	–0.098**
	(0.015)	(0.030)	(0.020)	(0.047)
Demand responses to information ($\Delta_n x$):				
More informative	–0.107*	0.036	–0.036	0.096**
	(0.055)	(0.026)	(0.058)	(0.039)
Less informative	0.082	0.021	0.159***	0.029
	(0.056)	(0.027)	(0.058)	(0.039)
Tax salience with information (θ_z) :				
θ_m	0.146		0.821***	
	(0.228)		(0.256)	
θ_l	0.387*		0.399	
	0.223		0.254	
N	10,650		10,817	
Misperception (in €per light bulb):				
b_{LED}	–1.25		–0.43	
$b_{Non-LED}$	2.62		1.03	
Misperception after provision of less informative signal:				
b_{LED}	–1.81		–1.86	
$b_{Non-LED}$	2.32		0.89	

Note: The sample is split by median share of votes for German environmental party “Die Grünen.” Estimation techniques and calculations are the same as in Table 4 but are done separately for each voter group. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A12: Welfare Effects with Heterogeneity in Green Party Support

Policy	Δ Utility non-Green consumers (€/consumer)	Δ Utility Green consumers (€/consumer)	Δ Profits (€/consumer)	Δ Externalities (€/consumer)	Δ Welfare (€/consumer)
More informative signal	0.11	0.06	0.20	1.14	–0.85
Less informative signal	–0.07	–0.15	0.58	0.63	–0.16
Optimal tax: t_{led} = –1.26 €/bulb, t_{Inef} = 1.12€/bulb	–1.59	–5.94	–4.14	–11.27	3.34

Note: The sample is split by median vote share for German environmental party "Die Grünen" to calculate consumer surplus for each voter group. Only subjects from zip codes with available voting data are included.

Table A13: Optimal Taxes with Heterogeneity in Green Party Support

Policy	Tax on LED bulbs (€/bulb)	Tax on Non-LED (€/bulb)
Tax policy in isolation	–1.26	1.12
Policy mix with more informative signal	–3.90	2.24
Policy mix with less informative signal	–0.67	3.37

Note: The table shows the optimal tax vector under heterogeneity given that political support for the Green party identify preference and belief heterogeneity.

Reduced-Form Results with Bulk Purchases Included

This subsection presents results without excluding bulk purchases. Bulk purchases were defined as the top 1 percent of light bulb sales.

Table A14: Average Treatment Effects on Purchase – Probability Bulk Purchases Included

	Probability to purchase
Information treatments:	
More informative	–0.0009
	(0.0006)
Less informative	–0.0003
	(0.0006)
Price discounts:	
LED	0.0006
	(0.0008)
CFL	0.0006
	(0.0008)
Halogen	0.0012
	(0.0008)
Incandescent	–0.0001
	(0.0008)
Baseline probability	0.0449
N	641,024

Note: The table shows average marginal effects from a probit regression of 1(Purchase) on pooled treatment variables. Day fixed effects are included. Standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A15: Average Treatment Effects on Purchase Probability – All Interactions and Bulk Purchases Included

	Probability to purchase
More informative	–0.0013
	(0.0014)
Less informative	–0.0004
	(0.0014)
LED	0.0006
	(0.0014)
CFL	0.0009
	(0.0014)
Halogen	0.0005
	(0.0014)
Incandescent	–0.0004
	(0.0014)
More informative & LED	–0.0005
	(0.0014)
More informative & CFL	–0.0003
	(0.0014)
More informative & Halogen	0.0008
	(0.0014)
More informative & Incandescent	–0.0016
	(0.0014)
Less informative & LED	0.0001
	(0.0014)
Less informative & CFL	–0.0004
	(0.0014)
Less informative & Halogen	0.0007
	(0.0014)
Less informative & Incandescent	–0.0001
	(0.0014)
Baseline probability	0.0449
N	641,024

Note: The table shows average marginal effects from a probit of 1(Purchase) on each of the 14 treatments. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A16: Average Treatment Effects on Demand – First Purchase Only – Bulk Purchases Included

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.079**	0.007	0.000	–0.013
	(0.033)	(0.006)	(0.018)	(0.017)
Less informative	–0.040	–0.002	–0.020	0.005
	(0.034)	(0.005)	(0.016)	(0.017)
Price discounts:				
LED	0.102**	–0.005	–0.024	0.005
	(0.044)	(0.008)	(0.023)	(0.020)
CFL	0.063	–0.006	0.008	0.020
	(0.046)	(0.007)	(0.026)	(0.022)
Halogen	–0.022	–0.005	–0.009	0.003
	(0.043)	(0.007)	(0.023)	(0.020)
Incandescent	0.006	–0.002	0.013	–0.002
	(0.042)	(0.008)	(0.025)	(0.020)
Control group mean	0.515	0.015	0.101	0.055
N	28,806	28,806	28,806	28,806

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on pooled treatments. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A17: Average Treatment Effects on Demand – All Interactions and Bulk Purchases Included

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.033	0.032**	0.020	0.011
	(0.071)	(0.014)	(0.042)	(0.044)
Less informative	0.024	0.003	0.029	–0.011
	(0.073)	(0.010)	(0.045)	(0.034)
Price discounts:				
LED	0.173**	0.009	–0.008	0.005
	(0.079)	(0.018)	(0.036)	(0.039)
CFL	0.123	0.012	0.025	0.040
	(0.077)	(0.013)	(0.043)	(0.044)
Halogen	–0.023	0.008	0.048	0.000
	(0.069)	(0.010)	(0.034)	(0.037)
Incandescent	0.058	0.003	0.039	–0.008
	(0.071)	(0.009)	(0.042)	(0.035)
Interactions:				
More informative & LED	0.068	0.009	–0.002	–0.008
	(0.075)	(0.010)	(0.038)	(0.036)
More informative & CFL	–0.004	–0.001	0.075	–0.011
	(0.076)	(0.012)	(0.047)	(0.035)
More informative & Halogen	–0.089	0.008	–0.017	–0.007
	(0.074)	(0.010)	(0.035)	(0.036)
More informative & Incandescent	–0.002	0.021	0.029	–0.013
	(0.071)	(0.014)	(0.038)	(0.036)
Less informative & LED	0.055	0.001	–0.013	0.018
	(0.073)	(0.008)	(0.037)	(0.041)
Less informative & CFL	0.059	0.007	–0.026	0.030
	(0.079)	(0.010)	(0.039)	(0.040)
Less informative & Halogen	0.038	0.004	–0.008	0.014
	(0.079)	(0.012)	(0.039)	(0.037)
Less informative & Incandescent	–0.046	0.006	0.018	0.015
	(0.073)	(0.013)	(0.043)	(0.039)
Control group mean	0.515	0.015	0.101	0.055
N	28,806	28,806	28,806	28,806

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on each of the 14 treatments. Only the first purchase a subject makes during the experimental period is included. Day and zip code fixed effects are included. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

Table A18: Average Treatment Effects on Demand – All Purchases and Bulk Purchases Included

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information treatments:				
More informative	–0.059*	0.004	–0.008	–0.011
	(0.032)	(0.006)	(0.017)	(0.016)
Less informative	–0.027	–0.003	–0.019	0.006
	(0.033)	(0.005)	(0.016)	(0.016)
Price discounts:				
LED	0.121***	–0.004	–0.016	0.004
	(0.042)	(0.008)	(0.022)	(0.019)
CFL	0.076*	–0.006	0.018	0.019
	(0.045)	(0.007)	(0.026)	(0.021)
Halogen	–0.029	–0.007	–0.003	0.002
	(0.042)	(0.007)	(0.022)	(0.018)
Incandescent	0.024	–0.003	0.022	–0.003
	(0.041)	(0.008)	(0.024)	(0.018)
Control group mean	0.514	0.015	0.098	0.051
N	31,387	31,387	31,387	31,387

Note: The table shows average treatment effects from an OLS regression of quantities purchased of a particular technology on pooled treatments. The first and all subsequent purchases of a subject are included. Standard errors are clustered on individual level. Day and zip code fixed effects are included. Robust standard errors are in parentheses.*,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

8.3 Additional Figures

All 14 Treatment Banners

Figure A1: Treatment: Less Informative Signal

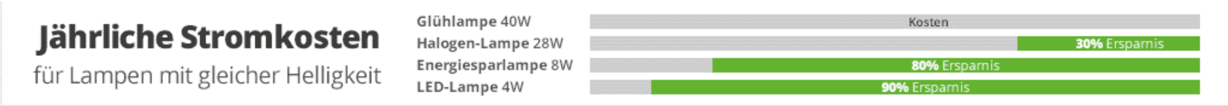


Figure A2: Treatment: More Informative Signal

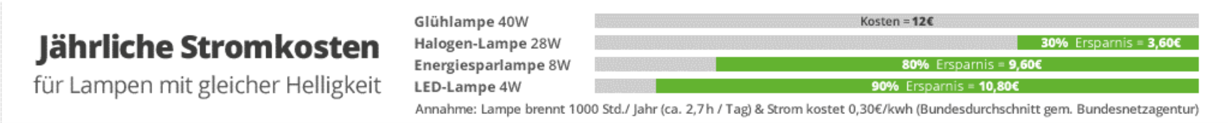


Figure A3: Treatment: Price Discount on LED Bulbs

Figure A4: Treatment: Price Discount on CFL Bulbs

Figure A5: Treatment: Price Discount on Halogen Bulbs

Figure A6: Treatment: Price Discount on Incandescent Bulbs

Figure A7: Treatment: Less Informative Signal and Price Discount on LED Bulbs

Figure A8: Treatment: Less Informative Signal and Price Discount on CFL Bulbs

Figure A9: Treatment: Less Informative Signal and Price Discount on Halogen Bulbs

Figure A10: Treatment: Less Informative Signal and Price Discount on Incandescent Bulbs

Figure A11: Treatment: More Informative Signal and Price Discount on LED Bulbs

Figure A12: Treatment: More Informative Signal and Price Discount on CFL Bulbs

Figure A13: Treatment: More Informative Signal and Price Discount on Halogen Bulbs

Figure A14: Treatment: More Informative Signal and Price Discount on Incandescent Bulbs

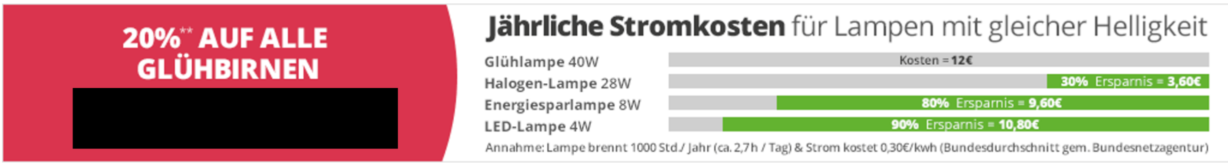


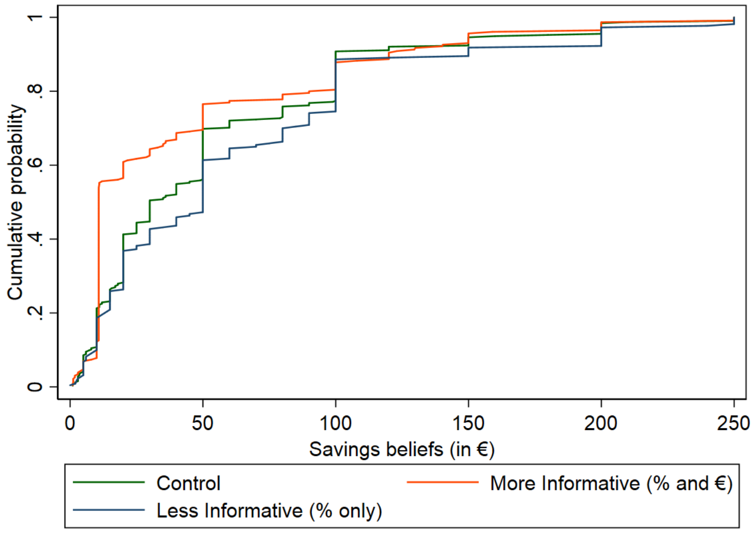
Figure A15: Second Study: Banner Inviting Website Visitors to Participate in the Survey

Figure A16: Placement of Treatments in Webstore

Note: This figure shows an excerpt of the online store to illustrate how the treatments were placed. The black censor bars protect the company's anonymity.

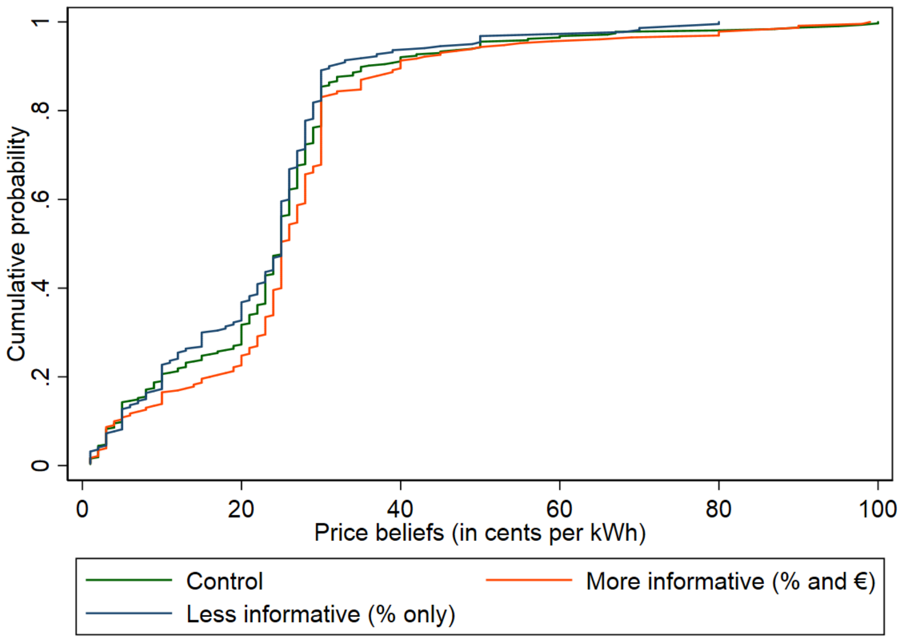
Beliefs

Figure A17: Savings Beliefs



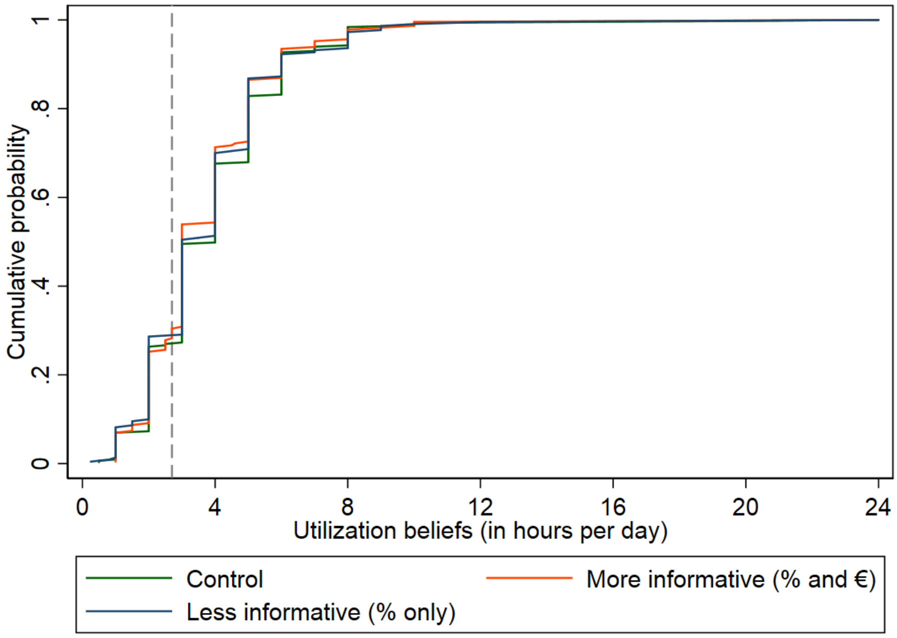
Note: The figure shows the empirical cumulative distribution functions of answers to the survey question on savings beliefs, for each experimental group. The question was, "How many euros would you save in annual electricity costs if you used a 4W LED light bulb instead of a 40W incandescent light bulb? Please state the annual electricity savings in euros." Subjects could answer by entering a number. To account for outliers, only subjects with savings beliefs below the 95th percentile are included.

Figure A18: Price Beliefs



Note: The figure shows the empirical cumulative distribution functions of answers to the survey question about the subject's electricity price, for each experimental group. The question was, "How many cents, do you think, are you paying per kilowatt hour? Please enter a number in cents." Subjects could answer by entering a number. To account for outliers, only subjects with savings beliefs below the 95th percentile are included.

Figure A19: Utilization Beliefs



Note: The figure shows the empirical cumulative distribution functions of answers to the survey question about the subject's utilization of a light bulb, for each experimental group. The question was, "How many hours are you using a light bulb on average per day? Please enter a number in hours." Subjects could answer by entering a number. To account for outliers, only subjects with savings beliefs below the 95th percentile are included.