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ABSTRACT

Information Nudges, Subsidies, and Crowding Out of Attention: Field Evidence from Energy Efficiency Investments*

How can information substitute or complement financial incentives such as Pigouvian subsidies? We answer this question in a large-scale field experiment that cross-randomizes energy efficiency subsidies with information about the financial savings of LED lighting. Information has two effects: It shifts and rotates demand curves. The direction of the shift is ambiguous and highly dependent on the information design. Informing consumers that an LED saves 90% in annual energy costs increases LED demand, but showing them that 90% corresponds to an average of 11 euros raises demand for less efficient technologies. The rotation of the demand curve is unambiguous: information dramatically reduces both own-price and cross-price elasticities, which makes subsidies less effective. The uniform decrease in price elasticities suggests that consumers pay less attention to subsidies when information is provided. We structurally estimate that welfare-maximizing subsidies are up to 150% larger than the Pigouvian benchmark when combined with information.

JEL Classification: D61, D83, H21, Q41, Q48

Keywords: information, nudges, optimal taxation, internality taxes, field experiments, energy efficiency, behavioral public economics

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1 Introduction

Governments frequently combine information provision with monetary incentives in a variety of markets. Energy-efficient products are subsidized by rebate programs and accompanied by energy efficiency labels. Sugar taxes are combined with food labels that assign different colors to groceries depending on how healthy they are. Tobacco taxes and warning labels on cigarette packs are implemented in combination. How do these informational interventions interact with monetary incentives? And what is the socially optimal design of information? Despite the ubiquity of information nudges, there is little evidence in the literature that can speak to these questions.

This paper provides a first set of answers using a large-scale field experiment in an online shop with over 640,000 subjects. We partner with one of Europe's largest online retailers for household lighting and randomize different information nudges that inform consumers about the energy savings of efficient LED lighting. In addition, we cross-randomize rebates on LEDs and alternative products to quantify the effects of Pigouvian subsidies with and without information nudges.

We test two different informational designs that vary in their coarseness of information. In one treatment, an information banner tells subjects that LEDs save 90% in annual electricity costs relative to traditional incandescents. In the other treatment, subjects see the same information but are also told that 90% translate to an annual average savings of around 11 euros. We refer to these treatments as the ”less informative” and ”more informative” nudge, respectively. This variation of informativeness is motivated by the observation that typical information nudges are noisy signals that only provide a relative ranking of products. For instance, knowing that a refrigerator is certified with an energy efficiency grade ”A” informs consumers that it saves costs relative to refrigerators with grade ”B”, but not how the difference in grades translates into monetary savings. One rationale behind this design is that it may be too costly to inform consumers with heterogeneous consumption patterns concisely. An alternative motive is that these policies are not just designed to resolve imperfect information but to persuade consumers to invest in energy efficiency as much as possible. 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 belief distortions. Our experiment evaluates whether more coarse information (in percentage) can be socially more desirable than more precise information (in percentage in euros).

We cross-randomize these two informational interventions with an energy efficiency rebate that reduces the price of LEDs by 20%. Energy efficiency rebates are a common policy in the US and the EU, and are typically posted price-exclusive. Our experimental design allows us to test how these product subsidies compare to information provision and how the effect of subsidies changes when combined with information nudges.

In addition, we cross-randomize the informational treatments with 20% discounts on alternative, less energy-efficient products (CFLs, halogen, and incandescents). We do this in order to identify all cross-price elasticities of LED demand and understand substitution patterns. Knowledge of all cross-price elasticities then allows us to estimate welfare-maximizing subsidies on LEDs and taxes on inefficient products.

Our main results provide two novel insights. First, the directional effect of information on demand and choice quality markedly depends on the label's design. Specifically, telling subjects that an LED bulb saves 90% in energy costs relative to an incandescent increases demand for LEDs by 24%. However, this effect vanishes when subjects are also informed that 90% translate into an average annual savings of approximately 11 euros. The more-informative nudge not only attenuates the effect on LED demand but also increases demand for less energy-efficient CFL technologies by around 300%.

A follow-up survey with store visitors 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 overestimate savings from LEDs, and showing subjects the savings only in percentage increases the degree of overestimation even further. These movements in beliefs are in line with the point estimates of demand responses from the main experiment and help us identify which nudge led to well-informed choices.

Leveraging a structural model, we find that the benefits to consumer welfare from more information are relatively small, while the increase in externalities could be substantial. This suggests that more coarse information provision may be socially desirable.

The second novel insight is that both informational interventions dramatically decrease price elasticities: The demand response to LED rebates drops by up to 60% if information nudges are added. As a result, energy efficiency subsidies need to be more than twice as large to generate the same demand response when information is provided. While the negative effect of information on price elasticities could be explained by nonlinearities in demand functions, a more plausible mechanism is that information crowds out the salience of subsidies. We consider this the most likely explanation because we find that information does not only reduce the own-price and cross-price elasticities of LED demand. Information also pushes virtually *all* own-price and cross-price elasticities of *all* alternative product categories towards zero. This overall drop in price elasticities is hard to reconcile with nonlinearities in demand functions alone.

The results on salience effects establish a novel trade-off for policymakers when choosing a combination of price- and non-price interventions: While information can decrease the distortions from biased beliefs, it introduces a salience bias, which can lower consumer welfare and raises optimal subsidies.

Based on the structural model, we estimate that welfare-maximizing subsidies can be more than twice as large as the Pigouvian benchmark when combined with one of the information nudges.

Contributions to the Literature This paper makes three main contributions. First, it combines a large-scale field experiment with a structural model to empirically study the optimal design of information nudges and evaluates whether less-informative nudges can be socially more efficient. Second, it shows how traditional product subsidies compare to information nudges. Third, it documents novel interactions between information and subsidies that are substantial in magnitude and change optimal policy-making.

Our findings add to a small body of the recent literature in behavioral public economics that quantifies optimal policies in the presence of belief distortions and other behavioral biases.[1] Bernheim and Rangel (2009), Mullainathan, Schwartzstein, and Congdon (2012), and Farhi and Gabaix (2020) develop general frameworks to integrate behaviorally motivated taxes and alternative non-price interventions ("nudges") into public finance. Empirically, previous studies have focused on price interventions, such as taxes on energy consumption (Allcott, Mullainathan, and Taubinsky 2014) or subsidies on energy-efficient appliances (Allcott and Taubinsky 2015), when consumers underestimate the benefits of energy efficiency. Different to these papers, our study shows how the design of information can be used as an alternative policy tool.

Prior work has used stated-choice experiments to study the effects of energy efficiency labels on choice quality (Davis and Metcalf 2016, Rodemeier, Löschel, and Kube 2017, Andor, Gerster, and Sommer 2020). While these studies provide important information, related evidence shows that hypothetical and incentivized choices can diverge substantially (List and Gallet 2001, Rodemeier 2023). Our paper advances this literature by studying actual (i.e., incentivized) purchase decisions in the field and by measuring welfare implications.

In the area of food consumption, contemporaneous and important studies investigate the effects of food labels on consumer choice (Dubois et al. 2021) and equilibrium outcomes (Barahona et al. 2023).[2] Our study is unique in that it shows how small variations in information design yield vastly different effects.

Our study is also the first to document that information can crowd out the effectiveness of traditional Pigouvian subsidies. This result implies that tax salience, as in Chetty, Looney, and Kroft (2009) and Taubinsky and Rees-Jones (2017), can be endogenous to information provision. This insight is important for optimal policy since it means that the size of optimal taxes and subsidies may be substantially larger in markets in which information labels are used. List et al. (2022) provides a meta-analysis comparing welfare effects of nudges to taxes and argues that studies should directly estimate interactions of these two policy tools. The negative interaction of information nudges and subsidies documented in our study is

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

[2] More broadly related to this, Dubois, Griffith, and O'Connell (2018) study the effect of a mandate that bans junk food advertisement.

not obvious ex-ante: Other behavioral interventions such as real-time feedback (Jessoe and Rapson 2014) and home energy reports (List et al. 2017) have been shown to *complement* financial incentives to conserve energy.[3]

At a foundational level, our structural parameter estimates inform leading models of salience (Bordalo, Gennaioli, and Shleifer 2013, Kőszegi and Szeidl 2013, Bordalo, Gennaioli, and Shleifer 2020) about the effect of information on attention to price interventions.

From an applied policy perspective, we provide novel evidence for the policy debates around the question of whether households underinvest in energy efficiency because they underestimate the associated savings. Previous research generally finds evidence both against and in favor of this hypothesis (e.g., Larrick and Soll 2008, Attari et al. 2010, Newell and Siikamäki 2014, Allcott and Sweeney 2017, Houde 2017, Allcott and Knittel 2019, Brandon et al. 2019, Löschel, Rodemeier, and Werthschulte 2022, d'Adda, Gao, and Tavoni 2020). Perhaps most related to our setting is the seminal study by Allcott and Taubinsky (2015) who derive optimal energy efficiency subsidies when consumers are poorly informed about the savings of energy efficiency. They show that information about the savings of CFLs relative to incandescents increases willingness-to-pay for CFLs in a survey experiment, and they estimate the optimal subsidy level based on this data. While their paper focuses on subsidies, we study information nudges as an important alternative policy tool and its interactions with subsidies.

The rest of the paper proceeds as follows. The experimental design is discussed in Section 2. We document reduced-form results in Section 3. In Section 4, we present results from a complementary survey that elicits savings beliefs of shop visitors. We then structurally estimate behavioral parameters of biased beliefs and inattention to subsidies in Section 5. Section 6 concludes.

2 Field Experiment

2.1 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 nudges regarding the monetary savings associated with buying more energy-efficient lighting technologies.

[3] Jessoe and Rapson (2014) find that household energy consumption decreases more to price hikes if consumers also receive real-time feedback about prices and consumption. List et al. (2017) show that home energy reports can increase the effectiveness of a reward program that incentivizes households to save energy.

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., lower carbon emissions), consumption choices may also cause uninternalized social costs. An optimal information policy weighs the benefits from more informed choices to consumer surplus with the associated change in externalities.

2.2 Design

The study was pre-registered at the AEA RCT registry.[4] 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.[5] 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 nudge, 2) a more informative nudge, or 3) no information. In addition, every visitor receives a 20% price discount on A) LED bulbs, B) CFL bulbs, C) halogen bulbs, D) incandescent bulbs, or E) does not receive a price discount.[6] We use English translations of the treatments in the main part of the paper and show the original versions in German in the Appendix.

We randomized price discounts not just for LEDs but also for less energy-efficient technologies in order to identify the matrix of own-price and cross-price elasticities. This allows us to estimate the size of optimal energy efficiency subsidies, taking into account substitution patterns between technologies.

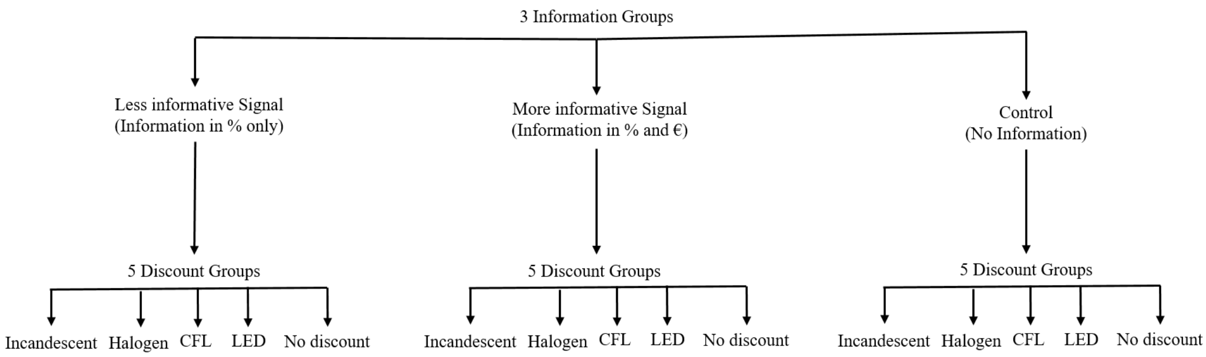
Information group 1 (less informative nudge): For subjects in group 1, the banner in Figure 2 is displayed at the top of the browser and contains information on the annual electricity savings of three lighting technologies (LED, CFL, halogen) in comparison to a traditional 40W incandescent light bulb. We use a bar chart to visualize the savings associated with each lighting technology. 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% 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 nudge provides subjects with

[4]The trial ID is AEARCTR-0002814. We pre-registered the main outcome variables of interest that are presented in this paper. We also pre-registered two additional outcome variables not discussed in the paper: 1) the "probability to buy a light bulb" (i.e., an extensive margin) and 2) the "watts of the purchased bulbs." Regarding 1), in an unreported regression, we find no effect of the treatments on the probability of buying a bulb. An exception is the LED discount that increases the probability by 2.5 percentage points with 90% confidence. Regarding 2), we learned that for some products, the company did not store information on watts, which causes missing values in the data. We, therefore, refrained from using it as an outcome variable. Finally, our sample size is smaller than expected because the company had overestimated the expected number of website visitors during the experimental period.

[5]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 a change in cookies rarely occurred during the experiment.

[6]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.

potentially useful information, it leaves substantial room for interpretation. For instance, it may still be unclear for consumers whether 90% savings translate into 1 or 100 euros per year. 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.

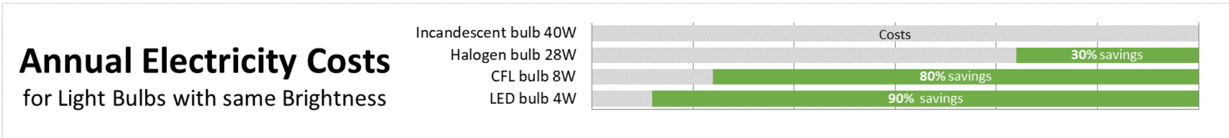
Importantly, the banner appeared on every subpage of the website and could not be clicked away by the visitor. This makes it particularly likely that the visitor saw and engaged with the information. The only subpage where the banner did not appear was at the checkout when the visitor eventually made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

Information group 2 (more informative nudge): Figure 3 shows the banner with the more informative nudge. 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 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 a classical economic perspective, this nudge is (weakly) more informative, as it involves more potentially relevant information. It may therefore lead to more informed choices than the nudge provided in group 1. However, it may also be the case that subjects do not properly process this information, possibly because they do not know how much they differ from the average consumer. We address these concerns in a second belief-elicitation experiment and find 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.[7]

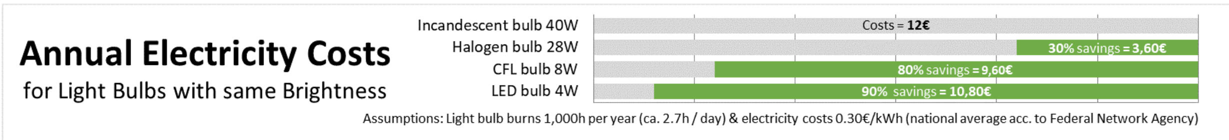
Information group 3 (no information): Subjects in this group receive no additional information on the financial benefits of energy efficiency other than the information already provided by the online retailer in the product description.

Figure 2: Treatment: Less Informative Nudge



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 B1.

Figure 3: Treatment: More Informative Nudge



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 B2.

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

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 B3. The black censor bars protect the company's anonymity.

This design generates 15 experimental groups: 1.A, 1.B, 1.C, 1.D, ..., 3.E. Figure 4 shows an example of the price discount on LED light bulbs. As an example of how we

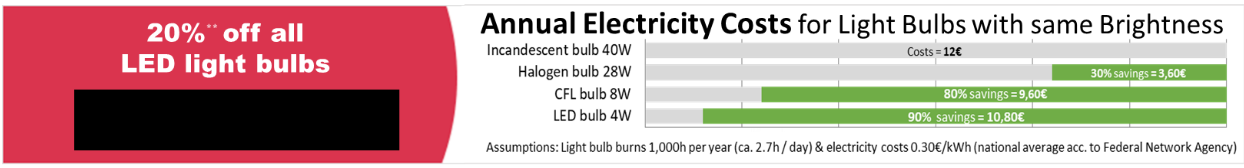
[7]Note that the online store already provides other relevant information for each product. Next to every light bulb, the consumer can see the associated lifetime of the bulb, the energy consumption in watts, and the bulb's brightness in lumens. While we could have provided more complex information, such as the calculated lifetime savings of each bulb, this would have required us to make strong assumptions on individual replacement behavior and to risk overwhelming or misinforming consumers.

combined price and informational treatments, Figure 5 illustrates the combination of the more informative nudge and a discount on LEDs. Here, the price discount is shown directly next to the informational intervention. The fact that information and the discount need to share the area of the banner captures the idea that space is a scarce resource when designing optimal policies. For example, the advertisement of many real-world energy rebates needs to share the space on product packages with energy efficiency labels.

The interaction effect of subsidies and information is ambiguous ex-ante. For example, if a consumer has strong preferences for incandescents and is also unaware of the savings of LEDs, then a discount on LEDs may not change her behavior. However, once she learns about the savings, she might become responsive to the discount. In this case, information nudges could increase price elasticities. Alternatively, information may reduce the price elasticity if it crowds out attention to the subsidy. This may be plausible, as well, since providing one rather than two stimuli can increase cognitive load for consumers.

An overview of all 14 treatment screens in the original version in German can be found in the Appendix. Figure B16 also illustrates how the banners were placed in the online store.[8]

Figure 5: Treatment: Combination of More Informative Nudge 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 B11. The black censor bars protect the company's anonymity.

2.3 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% 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.

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

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% of light bulb sales. Since our theory provides a 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 1 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 control group, the average customer who made a purchase bought 0.51 LED bulbs. Put differently, approximately every second consumer purchased one LED, on average. A remarkable result is that even in the control group, many 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.[9] These numbers are surprising in 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.

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. We do not find statistically significant differences across treatment arms for any of these variables.

[9]Remember that the online shop does not only sell light bulbs but also various other products. Therefore, the means of LEDs, CFLs, halogen, and incandescents do not need to add up to a number equal to or greater than one. Adding up the means of the technology purchases, we find that the average customer buys 0.72 light bulbs, implying that not every customer buys a bulb.

Table 1: Summary Statistics

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
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
Number of sessions on website	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)
Number of light bulbs purchased:															
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)
Other order characteristics:															
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)
N	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 nudge, less informative nudge, or no information (control), respectively. Standard deviations are reported in parentheses.

3 Reduced-Form Results

3.1 No Selection into Subsample of Buyers

In order to quantify the causal effect of the treatments on demand for different light bulbs, we first need to ensure that the treatments did not cause differential selection of subjects into the pool of buyers. In the Appendix, we show that among the sample of 641,024 website visitors, none of the treatments affected the probability of buying at the store, such that differences in product demand conditional on buying at the store have a causal interpretation (see Table B1).

3.2 Demand for Lighting Technologies

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

$$y_{ij} = \alpha_j + \tau_j D_i + \sum_n \left(\beta_j^n I_i^n + \delta_j^n I_i^n D_i\right) + \psi_j DAY_i + \nu_j ZIP_i + \epsilon_{ij}, \tag{1}$$

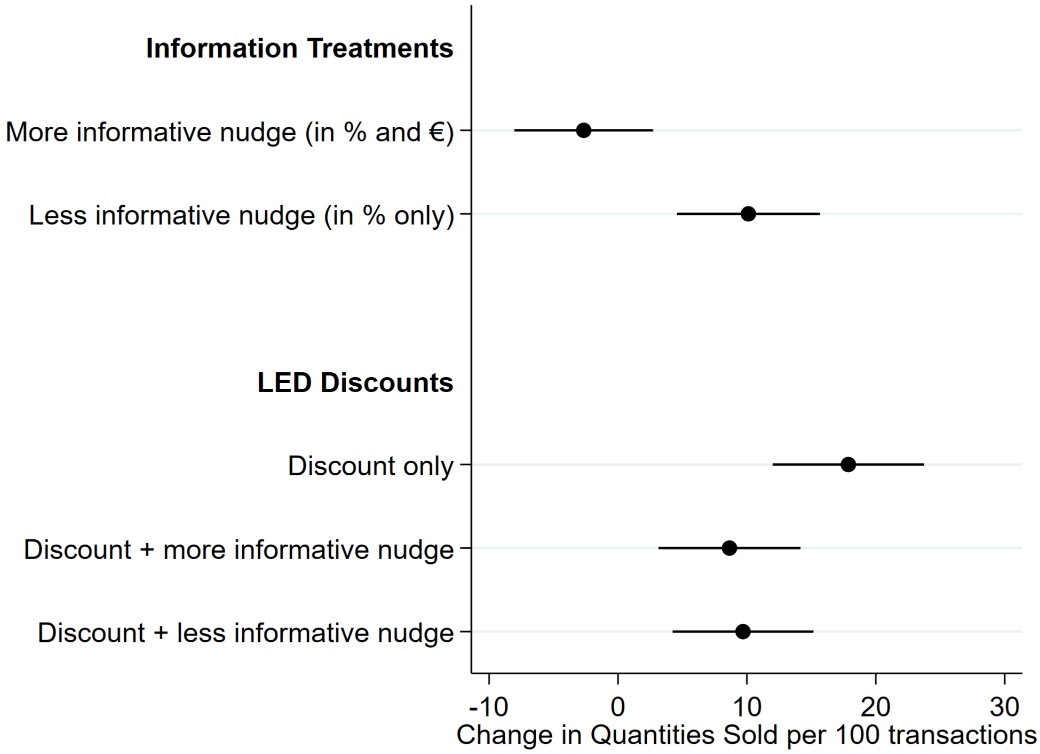
where y_{ij} are quantities purchased of light bulb technology j by consumer i during her first purchase. D_i is a vector indicating the discount treatments. I_i^n is an indicator for information treatment $n \in \{l, m\}$, where l and m abbreviate the less and more informative nudge, respectively. The treatment effects of discounts and nudges in isolation are, respectively, given by τ_j, β_j^l, β_j^m. The interaction term δ_j^n measures how the effect of discounts changes when information nudge n is added. ZIP_i and DAY_i are indicator vectors for the customer's zip code and day of purchase, respectively.

To ease readability, we multiply all coefficients and the regression constant by 100. The coefficients, therefore, report treatment effects per 100 transactions.

3.2.1 Effect of Information Nudges and LED Subsidies on LED Demand

We first visualize some important findings in Figure 6 by plotting the effects of information nudges and LED subsidies on LED demand. These are the treatments and the outcome variable that are most policy relevant.

Figure 6: Effect of Information Nudges and LED Subsidies on LED Demand



Note: The figure shows regression coefficients for information nudges and LED discounts, with LED bulbs as the outcome variable. The bars represent standard errors.

The more informative nudge that provides information in both percentages and euros has a negative coefficient of around 2.7 bulbs per 100 transactions. This effect is relatively noisy and not significant. Hiding the information in euros by providing the less informative nudge increases demand by around 10 bulbs per 100 transactions—a relative treatment effect of 24%. This effect is significant at the 10-percent level.

The difference between the more and less informative nudge is significant at the 1-percent level. The large difference in the coefficients appears remarkable as the two nudges only slightly differed in terms of content. This suggests that the directional effect of information provision is highly dependent on its design. We show in Section 4 that these point estimates of demand changes are in line with changes in consumers' beliefs about the savings of LEDs.

Figure 6 also shows that providing consumers with an LED discount (but no information) is the most effective intervention and causes a highly significant increase in LED demand by 18 LEDs per 100 transactions. This corresponds to an increase of 42% relative to baseline demand and implies a large own-price elasticity of –2.1.

An important finding is that this elasticity drops dramatically once information is added to the discount. Both coefficients at the bottom of the figure are only half as large and imply an increase in demand by around 10 LED bulbs per 100 transactions. Thus, information cuts own-price elasticities down to –1, making energy efficiency rebates less effective.

While this rotation in the demand curve due to information could be explained by nonlinearities in the demand function, we argue that this is an unlikely explanation on its own. As we show next, information pushes virtually *all* own-price and cross-price elasticities of *all* products towards zero. This pattern is hard to reconcile with nonlinearities in demand curves alone but rather suggests that information and discounts compete for attention.

3.2.2 Other Effects

Table 2 provides results from the four regressions of quantities demanded on the 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 following eight rows are interaction dummies. The third from last row reports p-values from an F-test for the joint hypothesis that all interaction terms are zero. The last two rows show baseline demand and sample size.

Table 2: Average Treatment Effects on Demand

	(1) LED (most energy-efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy-efficient)
Information Treatments:				
More Informative Nudge (in % and €)	-2.660	3.300**	-0.591	0.415
	(5.414)	(1.284)	(2.126)	(1.167)
Less Informative Nudge (in % only)	10.116*	0.675	-0.812	2.361
	(5.575)	(0.793)	(2.260)	(1.442)
Price Discounts:				
LED	17.873***	0.067	0.273	1.593
	(5.906)	(0.883)	(2.511)	(1.403)
CFL	9.555*	1.009	0.935	3.615**
	(5.413)	(0.920)	(2.254)	(1.740)
Halogen	0.162	0.429	2.767	1.240
	(5.092)	(0.743)	(2.133)	(1.468)
Incandescent	5.640	0.522	0.564	1.838
	(5.234)	(0.607)	(2.241)	(1.279)
Effect of Information on Discount Effectiveness:				
More Informative × LED	-6.562	-2.382	-0.381	-1.406
	(8.229)	(1.558)	(3.382)	(1.965)
More Informative × CFL	-2.922	-3.782**	2.934	-3.687*
	(7.751)	(1.639)	(3.244)	(2.113)
More Informative × Halogen	-2.794	-2.684*	-2.988	-0.328
	(7.391)	(1.601)	(3.132)	(1.740)
More Informative × Incandescent	-3.145	-2.404	1.582	-2.272
	(7.638)	(1.530)	(3.198)	(1.994)
Less Informative × LED	-18.290**	-0.526	1.346	-3.208
	(8.286)	(1.155)	(3.541)	(1.987)
Less Informative × CFL	-14.060*	-0.714	-2.701	-6.056***
	(7.964)	(1.221)	(3.113)	(2.134)
Less Informative × Halogen	-9.409	-0.765	-0.882	-2.798
	(7.654)	(1.171)	(3.141)	(2.116)
Less Informative × Incandescent	-16.620**	-0.793	-0.128	-3.970**
	(7.633)	(1.326)	(3.217)	(1.895)
p-value for h_0 : all interaction terms $= 0$	0.073	0.100	0.973	0.017
Control Group Mean	42.850	1.088	7.927	1.865
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. Coefficients and the control group mean are multiplied by 100 for readability. 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.

Column 1 shows that all interaction effects between information nudges and discounts have a negative sign. While some interaction terms in column 1 are not statistically significant at conventional levels, they are jointly significant at the 10-percent level, as shown in the third from last row. The effect of the less informative nudge on the cross-price elasticities with respect to CFL and Incandescent discounts are individually significant at the 10- and 5-percent level, respectively. Thus, we find strong evidence that information also reduces cross-price elasticities.

In fact, looking at columns 2-4, we find that almost every interaction term between information and price discounts has a negative sign. These negative effects are jointly significant for CFL demand at the 10-percent level (see column 2) and for incandescent demand at the 5-percent-level (column 4). If information changed elasticities simply because demand curves are nonlinear, we would not expect a negative coefficient on all own-price and cross-price elasticities. Instead, these patterns suggest that information and discounts compete for attention.

We also find a puzzling positive effect of the CFL discount on LED demand, significant at the 10-percent level. While this may suggest that the two technologies are complements, we think other mechanisms are more likely to be at play. One possible explanation is that discounts on light bulbs have a "reminder effect:" They remind consumers that they need a light bulb (CFLs, but also other bulbs), and, therefore, a discount on CFLs may increase demand for LEDs. This interpretation would mean that our estimated elasticities are lower bounds of the true cross-price elasticities. More generally, one should note that positive cross-price elasticities between obvious substitutes are not a specific issue of our study but represent a common measurement error problem in demand estimation (see, for example, Bucklin, Russell, and Srinivasan 1998).

Column 2 shows that the more informative nudge causes some consumers to choose the medium-efficient technology, as CFL demand increases by 3.3 bulbs per 100 transactions. This is a large relative treatment effect of 300%, albeit compared to a very low baseline demand. Again, we find evidence that information changes own- and cross-price elasticities since all interaction terms in column 2 are negative. While for LEDs, the reduction in attention to subsidies was mostly driven by the less informative nudge, for CFLs, the more-informative nudge crowds out attention to subsidies more severely. This is particularly true for the own-price elasticity and the cross-price elasticity with respect to halogen subsidies. All interaction terms are jointly significantly different from zero at the 10% level, as previously discussed.

Column 3 shows that there is no noticeable effect of any of the treatments on halogen demand. As with the previous technologies, almost all interaction terms have a negative sign.

For incandescent demand in column 4, the less informative nudge reduces the effectiveness of the incandescent discount as the own-price elasticity moves towards zero. We also observe a surprising positive cross-price elasticity with respect to the CFL discount. This may be a result of the low baseline demand for incandescents which increases the probability of false positives. The positive relationship disappears in the other two subgroups that receive one of the information treatments.

In sum, we find that the less informative nudge increases demand for LEDs, while the more informative nudge raises demand for alternative, less efficient CFLs. Both information nudges substantially lower own-price and cross-price elasticities of various technologies, suggesting that information reduces the salience of subsidies.

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.[10] Several months after the end of the first experiment, another banner (depicted in Figure B15) was shown on the website inviting consumers to take part in a three-question survey. Participation was incentivized with a discount of 20% 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 nudge, S2) the more informative nudge, or S3) no information. On the next page, participants were asked a question on their savings beliefs of LEDs relative to incandescent light bulbs, their individual electricity price, and their utilization habits of light bulbs.[11]

They were 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. This results in a sample of 765 subjects. Over 77% 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. Recall that answers were not incentivized such that this number may well overstate subjects' true beliefs. Instead, *differences* in savings beliefs between treatment groups are a more reliable measure.[12] In line with the negative coefficient for LED sales in Table 2, providing consumers with the more informative nudge shifts savings beliefs downwards. The less informative nudge also moves beliefs, albeit in the opposite direction. This shift is in line with the positive treatment effect coefficient of the less informative nudge on LED demand observed in the main experiment. The average treatment effects of the less and more informative nudge are significant at the 5% and 10% level, respectively. The more informative nudge decreases expected annual savings by €9.53, whereas the less informative nudge increases estimated savings by €9.20.

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

[11] See Figure B17 in the Appendix for the original questions in German.

[12] For example, the missing incentives in the survey might cause consumers to invest less effort into calculating their savings, which creates a measurement error. Differences in savings beliefs across treatments may still be a good approximation to true differences in beliefs, as long as the measurement error does not vary too much across treatment arms. Even when the error does vary substantially, the qualitative results remain the same if differences in the measurement error do not change the order of the mean in savings beliefs across treatments.

An open question is whether the more informative nudge 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:

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 7 plots the empirical CDFs of this difference for the three experimental groups. Most consumers in the control group overestimate their savings, and this overestimation exacerbates with the less informative nudge. The distribution of belief distortions for subjects who saw the more informative nudge is shifted toward zero relative to the control group.

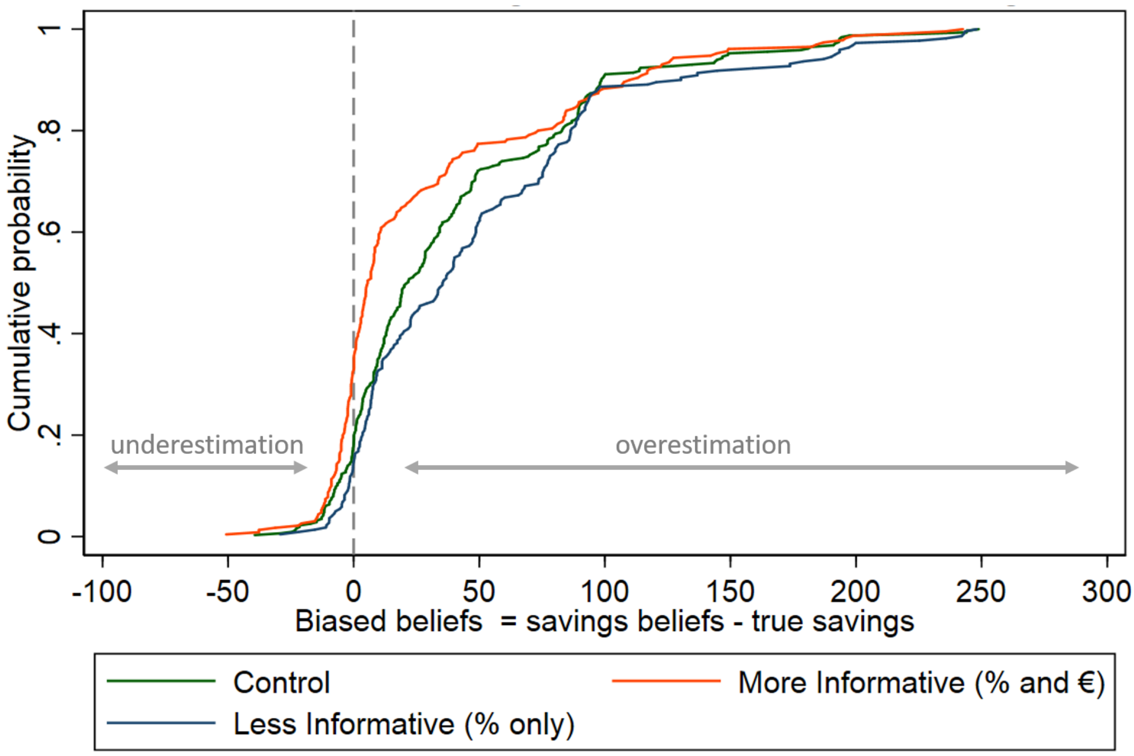
These results indicate that the more-informative nudge, in fact, led to more-informed beliefs, even after adjusting for individual heterogeneity.

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 7: Bias in Beliefs about LED Savings



Note: The figure shows the empirical cumulative distribution functions of the error in savings beliefs for each experimental group. We calculate the error as the difference between the 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.

5 Structural Model

In this section, we estimate structural parameters of biased beliefs and inattention to subsidies with the data from the experiment. This exercise is useful as it is informative about the efficiency effects of information provision, as well as about the size of optimal subsidies when combined with information.

5.1 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 subsidies $\mathbf{s} = (s_1, s_2, ..., s_J)$. We make the standard assumptions regarding the properties of v: we assume that $\frac{\partial v}{\partial x_j} > 0$ and $v(\mathbf{x})$ 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. We make no assumption on the joint distribution of states, $\mathbf{F}(\omega)$.

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, $Y(\mathbf{s}) = Z - T(\mathbf{s})$, is income, Z, minus income tax, $T(\mathbf{s})$. Taxes are recycled in lump-sum to finance subsidies, and the government maintains a balanced budget. Preferences are described by

$$u(\mathbf{p}, \mathbf{s}) = v(\mathbf{x}) + Y(\mathbf{s}) + (\omega - \mathbf{p} + \mathbf{s})'\mathbf{x}. \tag{2}$$

The consumer expects the states of the world to be $\hat{\omega}(\mathbf{n}) = (\hat{\omega}_1(n_1), \hat{\omega}_2(n_2), ..., \hat{\omega}_J(n_J))$, where the expectation about each product j is a function of an information parameter n_j. We call the difference $\mathbf{b}(\mathbf{n}, \omega) = \hat{\omega}(\mathbf{n}) - \omega$ the consumer's belief distortion or misperception about ω. We assume that $\hat{\omega}_j(n_j)$ is differentiable in n_j, and we refer to the vector $\mathbf{n} = (n_1, n_2, ..., n_J)$ as an information nudge.

We denote the parameter that captures the salience of the subsidy by $\theta(\mathbf{n})$ 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 subsidy than to an equivalent decrease in price. We make the specific assumption that $\theta(\mathbf{0}) = 1$ such that consumers are attentive to subsidies when no information is provided.[13]

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

$$\mathbf{x}(\mathbf{p}, \mathbf{s}, \mathbf{n}) = \arg\max_{\mathbf{x}} \left\{ u(\mathbf{p}, \mathbf{s}) - (\underbrace{\mathbf{b}(\mathbf{n}, \omega)}_{\text{belief distortion}} + \underbrace{(1 - \theta(\mathbf{n}))}_{\text{subsidy salience}} \mathbf{s})'\mathbf{x} \right\}. \tag{3}$$

Demand maximizes utility when there are no belief distortions, $\hat{\omega}(\mathbf{n}) = \omega$, and consumers are fully attentive to subsidies, $\theta(\mathbf{n}) = 1$.

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).

Let the vector of demand responses to an information nudge be $\mathbf{\Delta x} = (\Delta x_1, \Delta x_2, ..., \Delta x_J)$, where $\Delta x_j = \int_{\mathbf{z}=\mathbf{n}}^{\mathbf{z}=\mathbf{n}+\mathbf{\Delta n}} \frac{dx_j(\mathbf{p},\mathbf{s},\mathbf{n},\omega)}{d\mathbf{n}} d\mathbf{z}$ is the demand response of product j to a change in the information policy from $\mathbf{n}$ to $\mathbf{n} + \mathbf{\Delta n}$. Furthermore, let $\mathbf{\Delta x}^*$ be the demand response to a fully informative nudge, $\mathbf{n}^*$, such that $\mathbf{b}(\mathbf{n}^*, \omega) = \mathbf{0}$.

The empirical analog to $\mathbf{\Delta x}$ is the vector of reduced-form treatment effects to our less informative nudge.[14] By contrast, we use demand responses to the more informative nudge to

[13] We view this assumption as reasonable in our empirical setting where the financial incentive comes in the form of a salient discount, which is presented on a large banner placed above all products in the online shop. While our analysis may be easily extended to cases where $\theta(\mathbf{0}) \neq 1$, we maintain this assumption to ease notation and for clarity.

[14] Alternatively, it could represent 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.

approximate $\mathbf{\Delta x}^*$.[15]

Furthermore, denote $\mathbf{E} = (\frac{dx_j}{dp_k}) \in \mathbb{R}^{I \times K}$ as the Slutsky matrix whose elements are the own-price and cross-price derivatives of demand. These are identified by our discount treatments without information nudges.

Finally, we denote by $\mathbf{E_n} = \theta(\mathbf{n})\mathbf{E}$ the Slutsky matrix when an information nudge $\mathbf{n}$ is provided. The Slutsky matrices under the more- and less-informative nudge are identified since we cross-randomized all discounts with the information nudges. The Slutsky matrix in the absence of information provision is given by $\mathbf{E} = \mathbf{E_0}$.

Proposition 1 establishes that we can identify belief and salience distortions through knowledge of $\mathbf{\Delta x}$, $\mathbf{\Delta x}^*$, $\mathbf{E}$, and $\mathbf{E_n}$.

Proposition 1. *Consider an information policy* $\mathbf{n}$ *that changes the misperception vector from* $\mathbf{b}$ *to* $\mathbf{b} + \Delta\mathbf{b}$. *We can approximate the change of the money-metric bias about* ω *by*

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

Similarly, we can approximate the pre-intervention bias by

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

The salience of subsidies under information policy $\mathbf{n}$ *is identified by*

$$\theta(\mathbf{n}) = \mathbf{E_n}\mathbf{E}^{-1}. \tag{6}$$

Proposition 1 shows that we can approximate the change in consumers' misperceptions through knowledge of the Slutsky matrix and the demand response to the associated information nudge. 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 nudge was implemented.

The salience of subsidies can be identified by comparing how demand responds to subsidies with and without information provision. Empirically, this implies that changes in demand elasticities, caused by information, identify θ.

We define social welfare, denoted W, as indirect utility net of tax transfers, plus firm profits and minus externalities. We denote marginal firm markups by $\mathbf{m} = (m_1, m_2, ..., m_J)$ and marginal externalities by $\boldsymbol{\epsilon} = (\epsilon_1, \epsilon_2, ..., \epsilon_J)$. The social welfare function is therefore given by

$$W = u(\mathbf{x}(\mathbf{p}, \mathbf{s}, \mathbf{n}), \mathbf{p}, \mathbf{t}, \omega) + (\mathbf{m} - \boldsymbol{\epsilon})'\mathbf{x}(\mathbf{p}, \mathbf{s}, \mathbf{n}). \tag{7}$$

[15] In the language of Bernheim and Rangel (2009), the empiricist takes a stance on the "welfare-relevant domain" in the observed data. While this may seem like a strong requirement, it is not a special property of our model, but it is inherent in *every* empirical welfare analysis that relies on revealed preferences.

The optimal subsidy vector is established in Proposition 2. Subsidies in equation 8 are set such that they correct any market frictions that remain after the nudge has changed consumers' beliefs. Importantly, $\mathbf{b}(\mathbf{n})$ is the bias vector *after* the information policy $\mathbf{n}$ has been implemented. If the information policy was fully informative, i.e. $\mathbf{b}(\mathbf{n}) = \mathbf{b}(\mathbf{n}^*) = 0$, then the optimal subsidy does not need to account for belief distortions. In this case, the optimal subsidy just needs to internalize externalities and markups.

However, it may also be the case that the nudge only partially reduced belief distortions, such that optimal subsidies need to take into account any remaining misperceptions.

Proposition 2. *An optimal subsidy vector, denoted* $\mathbf{s}^*(\mathbf{n})$*, is given by*

$$\mathbf{s}^*(\mathbf{n}) = -\frac{\mathbf{b}(\mathbf{n}) + \boldsymbol{\epsilon} - \mathbf{m}}{\theta(\mathbf{n})}. \tag{8}$$

Note that optimal subsidies need to be larger when information decreases the salience of subsidies (i.e., when $\theta(\mathbf{n}) < 1$) since every market friction is scaled by the salience parameter. In a standard model without belief biases and markups, the optimal policy would simply be Pigou taxes, $\mathbf{s}_{Pigou} = -\boldsymbol{\epsilon}$. However, in the presence of information provision, Pigou taxes no longer yield the first-best outcome because the respective demand response is not large enough to internalize externalities.

5.2 Moment Conditions and Model Constraints

We estimate the parameters from Proposition 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 pool all non-LED technologies into one category such that we have two technologies $j \in \{\text{LED, Non-LED}\}$. The variable "Non-LED" is created by summing up demand for CFLs, halogen, and incandescent light bulbs. Pooling variables is helpful because the baseline demand for CFLs, halogen, and incandescent light bulbs is low, which results in imprecision from small cell variation. We therefore have two price discounts $d \in \{\text{LED, Non-LED}\}$ and three informational groups $n \in \{\text{c, l, m}\}$, where c represents no information (control group), l the less informative nudge, and m the more informative nudge. 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.[16]

Let P_i^n 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 n. 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_{jn}^k as the constant demand derivative of light bulb technology j

[16] We calculate the absolute price reduction for every light bulb technology by multiplying the 20% discount for each 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.

with respect to a price change in technology k when information policy n is provided. Within each informational state, there are two parameters for every j, and we list these in the 2×1 vector ξ_{jn}. The subsidy salience parameter is θ_z for $z \in \{l, m\}$.

Further, let $\Delta b_j = (\Delta_l b'_j, \Delta_m b'_j)$ be the 2×1 vector of changes in belief distortions about product j induced by the two informational treatments. By assumption $\Delta_m b'_j = -b_j$, i.e. the more informative nudge de-biases beliefs. We denote by I_i the 2×1 vector indicating whether subject i was in any of the informational groups.

Baseline demand for j in the absence of price discounts and information nudges is denoted by λ_j.

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

$$\mathbb{E}[P_i \left(y_{ij} - \lambda_j - \xi'_{jc} P_i^c - \theta_m \xi'_{jc} P_i^m - \theta_l \xi'_{jc} P_i^l - \Delta b'_j \xi_{jc}\right)] = 0 \tag{9}$$

and two moment conditions for the informational treatments,

$$\mathbb{E}[I_i \left(y_{ij} - \lambda_{ij} - \xi'_{jc} P_i^c - \theta_m \xi'_{jc} P_i^m - \theta_l \xi'_{jc} P_i^l - \Delta b'_j \xi_{jc}\right)] = 0. \tag{10}$$

Note that the moments impose the theory-driven constraints on the own-price and cross-price demand slopes between informational treatments $\xi^j_{kc} = \theta_m \xi^j_{km} = \theta_l \xi^j_{kl}$. The model also requires us to restrict the Slutsky matrix to be symmetric within each informational state: $\xi^k_{js} = \xi^j_{ks}$.

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

5.3 Estimation Results

5.3.1 Belief Distortions

Table 4 shows the results of the structural estimation described in the previous section. In row 1 of the table, we document the vector of belief distortions, i.e. b. This is identified by the treatment effects of the more informative nudge and the price elasticities. The average consumer overvalues LEDs by 57 cents per bulb (around 6% of the sales price) and undervalues less efficient alternatives by 67 cents per bulb (around 17% of the sales price). The effect on LED demand is not statistically significant, but the t-statistic is relatively large (around 1.36). The effect on Non-LEDs is significant at the 5%-level.

The second row shows how the bias vector changes by $\mathbf{\Delta b}$ if consumers are provided with the less informative nudge. This exacerbates the overvaluation of LEDs by 86 cents per bulb and slightly decreases the undervaluation of less efficient alternatives by 16 cents per bulb. Here, the effect on LED demand is significantly different from zero, while the effect on Non-LEDs is not.

Adding up the two vectors, $\mathbf{b} + \mathbf{\Delta b}$ tells us consumers' misperception in the presence of the less-informative nudge. Consumers now 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.

While the less informative nudge distorts consumer choices, it is likely to increase social welfare relative to the more informative signal. Assuming a social cost of carbon of USD 35 per ton of CO_2 (Nordhaus 2018) as the externality, we calculate that the marginal externalities equal 1.35 euros per LED bulb and 4.60 euros per Non-LED bulb.[17] Since an LED lasts 4.05 times longer than the average Non-LED, the assumed counterfactual external damage to buying one LED equals 4.60 euros $\times\ 4.05 = 18.63$ euros.[18] Thus, externalities create a much larger distortion than informational biases. Therefore, it may be optimal to provide consumers with less information, which only slightly distorts consumer surplus but substantially reduces externalities.[19]

These findings provide evidence that coarse information provision can be socially more efficient. This insight may explain the ubiquity of coarse labels in many markets, such as energy efficiency grades, coarse food labels, and health warnings on cigarette packages.

5.3.2 Inattention to Subsidies

The fourth and fifth rows of the table show how consumers respond to subsidies in the absence of information. The own-price demand derivatives, ξ^j_{jc}, are large and highly statistically significant. The symmetric cross-price derivative, ξ^k_{jc}, is economically small and statistically insignificant, consistent with most of the reduced-form estimates. The fifth and sixth rows of the table quantify how much information reduces the demand responses to subsidies. To test whether the parameters are different from one, i.e. from the full attention benchmark, we subtract each salience parameter from one.

Both coefficients are far from one. Under the more informative nudge, consumers' probability of paying attention to the subsidy is only $\theta_{more} = 0.55$, implying the nudge cut demand

[17] These assumptions are also supported by lower bounds of the social cost of carbon estimated from willingness-to-pay data (Rodemeier 2023).

[18] 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. According to the company, the average LED offered in the store uses 5W and last 15 years, while the average Non-LED bulb uses 69W and lasts 3.7 years. The average German household uses a light bulb for around 1,000 hours per year. We calculate externalities over 15 years, i.e. over 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 marginal externality of such a bulb is therefore 4.60 ($= 69 \times 0.02 \times 0.9 \times 3.7$) euros.

[19] In an analysis that is part of a longer version of this paper, we estimate policy counterfactuals and find that social welfare decreases with more information provision.

Table 4: Structural Parameters

	LED	Non-LED
Pre-intervention bias identified by more informative nudge:		
$\mathbf{b}$	-0.565	0.668**
	(0.416)	(0.304)
Change in bias caused by less informative nudge:		
$\mathbf{\Delta b}$	-0.862**	-0.164
	(0.406)	(0.280)
Price elasticities:		
ξ^j_{jc} (own-price)	-0.094***	-0.077***
	(0.018)	(0.027)
ξ^k_{jc} (cross-price, symmetric)	-0.019	
	(0.012)	
Inattention to subsidies with information nudges :		
$1-\theta_{more}$	0.449***	
	(0.171)	
$1-\theta_{less}$	0.616***	
	0.177	
N	28553	

Note: 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. Robust standard errors are in parentheses. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

elasticities in half. The less informative nudge has an even more negative effect on subsidy salience, $\theta_{less} = 0.38$. This means that demand elasticities fall by 62% when the less informative nudge is provided, making price interventions less effective. Both salience effects are statistically significantly different from one at the 1%-level.

The observation that the less informative nudge has a larger crowding-out effect on attention is surprising since it contains less information. One potential explanation is that the more informative nudge entails some information in monetary units and therefore keeps a larger share of consumers attentive to price discounts than the less informative nudge. This interpretation can be captured by more micro-founded models of salience, such as Bordalo, Gennaioli, and Shleifer (2021).

5.3.3 Optimal Subsidies with and without Information Nudges

We illustrate the importance of our results by calculating optimal subsidies with and without information nudges. We use equation 8 to calculate optimal subsidies. We again assume externalities of 1.35 euros per LED bulb and 4.60 euros per Non-LED bulb.

We obtain information on marginal markups of each product by the firm. The median marginal markup of an LED and a Non-LED are 3.45 euros and 1.66 euros, respectively.

Table 5 shows the optimal tax policy in isolation and in combination with informational interventions.[20] If no information nudge is provided, the optimal tax vector involves a tax on less efficient alternatives of 2.26 euros per bulb and a sizable subsidy on LEDs of 1.54 euros per bulb. The reason these values are both closer to zero than a tax that only corrects markups and externalities is that the information bias partially replaces the need for taxes. That is, consumers' overvaluation of LEDs and undervaluation of Non-LEDs internalizes parts of the externalities and markups.

When combined with information, taxes and subsidies need to increase dramatically to maximize welfare. When the more informative nudge is implemented, the optimal subsidy on LEDs increases to 3.81 euros and the optimal tax on less efficient alternatives to 5.32 euros. Standard errors are larger because there is additional uncertainty from the inattention parameter, θ_{more}, which is not present when estimating subsidies and taxes in isolation.

Under the less informative nudge, the optimal subsidy on LEDs is 1.75 euros per bulb, and the optimal tax on inefficient alternatives is 6.32 euros per bulb. The subsidy on LEDs decreases as we move from the more to the less informative nudge because reducing the informativeness increases the overvaluation of LEDs which reduces the optimal subsidy (and thereby also its statistical significance). In this particular aspect, the less informative nudge is complementary to the subsidy. However, relative to no information provision, the point estimate still increases because of the reduction in subsidy salience induced by information.

[20]Standard errors are calculated using the delta method. We first bootstrap the standard errors of median profits. Since we do not have information on the uncertainty of the average external damages, we assume that the mentioned externality values are the true external damages.

In sum, information nudges generally increase the size of optimal taxes and subsidies substantially. It is, therefore, not straightforward that the optimal policy consists of a mix of taxes and nudges. Instead, it may well be optimal to use taxes and subsidies without information nudges.

Table 5: Optimal Taxes & Subsidies

Policy	Tax on LED (€/bulb)	Tax on Non-LED (€/bulb)
Tax Policy in Isolation	-1.54***	2.26***
	(0.52)	(0.40)
Policy Mix with more-informative nudge	-3.81**	5.32***
	(1.55)	(1.89)
Policy Mix with less-informative nudge	-1.75	6.32***
	(1.33)	(0.97)

Note: The table shows optimal taxes and subsidies for the three different policies. Positive values indicate a tax on the respective good, negative values indicate a subsidy. Standard errors are obtained by the delta method. For more information, see footnote 20. *,**,***: significant at $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively.

6 Conclusion

How do information nudges interact with classical price interventions, and what is their optimal design? We take these questions to the field and address a phenomenon frequently attributed to informational biases: consumers' allegedly low investment in energy efficiency. In cooperation with one of Europe's main appliance retailer for household lighting, we provide consumers with information nudges regarding the financial benefits of energy efficiency and systematically vary the informativeness of these nudges. By cross-randomizing subsidies with nudges, we identify how these policy tools can substitute or complement each other.

We find that information both shifts and rotates demand curves. The direction of the shift is ambiguous ex-ante and turns out to be highly design-dependent. Coarse information disclosure boosts demand for LEDs by 24%, while more precise information increases demand for less energy-efficient CFL bulbs by 300%.

Using a complementary survey to elicit beliefs, we find that the more-informative nudge causes more accurate beliefs, while the less-informative nudge distorts beliefs. These survey results inform our structural model in identifying a benchmark for well-informed choices. We show that less information is likely to be more socially efficient even though it slightly distorts consumer choices. The reason is that the welfare loss from informational biases is relatively small, while consumers' overvaluation of LEDs creates substantial societal benefits from reduced externalities.

The effect of information on the slope of the demand curve is strictly negative, both for the more and the less informative nudge. The magnitudes are large: information provision reduces price elasticities by up to 62%. We find that virtually all own-price and cross-price elasticities have a negative interaction coefficient with information nudges. Our interpretation of this pattern is that these two stimuli compete for attention, such that information reduces the salience of subsidies.

Leveraging the structural model, we estimate that optimal subsidies and taxes may have to be more than twice as large as the Pigouvian benchmark when combined with information nudges.

From an applied policy perspective, our study has implications for the evaluation of different information designs chosen by governments. For example, 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 provides a similar ranking but also explicitly informs consumers about the average annual operating costs. Our study does not evaluate these particular labels but shows that more informative labels are not necessarily optimal for social welfare. Our results further highlight that it is crucial to evaluate the interaction of these labels with traditional price interventions, such as the widely-used energy efficiency rebates in the US.

From a methodological perspective, our structural model and experimental design can be applied to any setting in which governments can use information. Examples include information on high-caloric groceries, sugary beverages, cigarette packs, 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.

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Appendix: For Online Publication Only

A Mathematical Appendix

Proof of Proposition 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 $G^i := v_i - p_i - b_i(n_i) + \theta(\mathbf{n})s_i = 0$. Totally differentiating G^i yields

$$dG^i = \sum_{k=1}^{I} \frac{\partial v_i}{\partial x_k} dx_k - dp_i + \theta(\mathbf{n})ds_i - \left(\frac{\partial b_i(n_i)}{\partial n_i} - s_i \frac{\partial \theta(\mathbf{n})}{\partial n_i}\right) dn_i + \sum_{l \neq i} \frac{\partial \theta(\mathbf{n})}{\partial n_l} s_i dn_l.$$

To find the effect of a change in an exogenous variable $z_j \in \{p_j, s_j, n_j\}$ 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

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

where we use the notation $\frac{\partial \mathbf{v}}{\partial \mathbf{x}} := \frac{\partial v_j}{\partial x_k} \in \mathbb{R}^{I \times K}$, $\frac{\mathbf{dx}}{\mathbf{dz}} := \frac{dx_j}{\partial z_k} \in \mathbb{R}^{I \times K}$ 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

$$\frac{dx_i}{dz_j} = -\sum_{k=1}^{I}(-1)^{i+k}\frac{\partial G^k}{\partial z_j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{k,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)}. \tag{11}$$

The derivative of demand for i with respect to the price of j is given by setting $dz_j = dp_j$ in equation 11:

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

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

Using equation 11, we can similarly derive the effects of a change in a policy instrument on demand for i. The effect of a change in the subsidy s_j by ds_j on demand for i is

$$\frac{dx_i}{ds_j} = -\theta(\mathbf{n})(-1)^{i+j}\frac{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}^{j,i}\right)}{\det\left(\frac{\partial \mathbf{v}}{\partial \mathbf{x}}\right)} \tag{12}$$

$$= -\theta(\mathbf{n})\frac{dx_i}{dp_j}. \tag{13}$$

The effect of a change in n_j by dn_j is

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

If all subsidies are zero, this simplifies to

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

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

$$\begin{aligned}\Delta x_i(\mathbf{s}=0) &\approx \Delta n_i\frac{\partial x_i}{\partial n_i} + \sum_{k\neq i}\Delta n_k\frac{\partial x_i}{\partial n_k} &(14)\\ &= \Delta b_i\frac{dx_i}{dp_i} + \sum_{k\neq i}\Delta b_k\frac{dx_i}{dp_k} &(15)\end{aligned}$$

for every i. In going from the first to the second line, we have used the fact that, if subsidies are zero, $\frac{dx_i(\mathbf{s}=\mathbf{0})}{dn_j} = \frac{\partial b_j}{\partial n_j}\frac{dx_i}{dp_j}$ and the first-order approximation $\Delta b_i \approx \frac{\partial b_i}{\partial n_i}\Delta n_i$. The system of linear equations given by equation 15 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

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

From equation 13 it also becomes clear that $\theta(\mathbf{n}) = \mathbf{E_n}\mathbf{E^{-1}}$. This completes the proof. □

Proof of Proposition 2

The optimal subsidy vector is obtained by setting $\nabla W = \mathbf{0}$:

$$\nabla W = \begin{pmatrix} (b_1 + m_1 - \epsilon_1 - \theta(\mathbf{n})s_1)\frac{\partial x_1}{\partial s_1} + \sum_{j \neq 1}(b_j + m_j - \epsilon_j - \theta(\mathbf{n})s_j)\frac{\partial x_j}{\partial s_1} \\ \vdots \\ (b_I + m_i - \epsilon_I - \theta(\mathbf{n})s_I)\frac{\partial x_I}{\partial s_I} + \sum_{j \neq I}(b_j + m_j - \epsilon_j - \theta(\mathbf{n})s_j)\frac{\partial x_j}{\partial s_I} \\ (b_1 + m_1 - \epsilon_1 - \theta(\mathbf{n})s_1)\frac{\partial x_1}{\partial n_1} + \sum_{j \neq 1}(b_j + m_j - \epsilon_j - \theta(\mathbf{n})s_j)\frac{\partial x_j}{\partial n_1} \\ \vdots \\ (b_I + m_i - \epsilon_I - \theta(\mathbf{n})s_I)\frac{\partial x_I}{\partial n_I} + \sum_{j \neq I}(b_j + m_j - \epsilon_j - \theta(\mathbf{n})s_j) \end{pmatrix} = \mathbf{0}, \tag{16}$$

which is fulfilled when $s_i^* = (b_i(n_i) + m_i - \epsilon_i)\,\theta(\mathbf{n})^{-1}$ for all i. In vector notation this is $\mathbf{s}^* = (\mathbf{b}(\mathbf{s}) + \mathbf{m} - \epsilon)\theta(\mathbf{n})^{-1}$. This completes the proof. □

B Additional Figures and Tables

All 14 Treatment Banners

Figure B1: Treatment: Less Informative Nudge

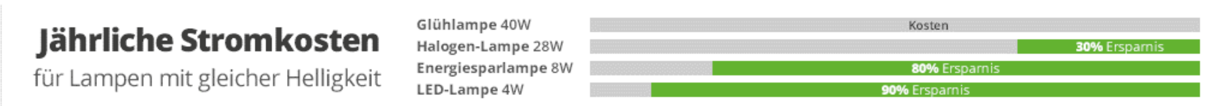


Figure B2: Treatment: More Informative Nudge

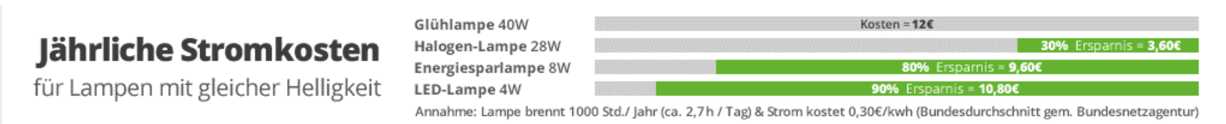


Figure B3: Treatment: Price Discount on LED Bulbs

Figure B4: Treatment: Price Discount on CFL Bulbs

Figure B5: Treatment: Price Discount on Halogen Bulbs

Figure B6: Treatment: Price Discount on Incandescent Bulbs

Figure B7: Treatment: Less Informative Nudge and Price Discount on LED Bulbs

Figure B8: Treatment: Less Informative Nudge and Price Discount on CFL Bulbs

Figure B9: Treatment: Less Informative Nudge and Price Discount on Halogen Bulbs

Figure B10: Treatment: Less Informative Nudge and Price Discount on Incandescent Bulbs

Figure B11: Treatment: More Informative Nudge and Price Discount on LED Bulbs

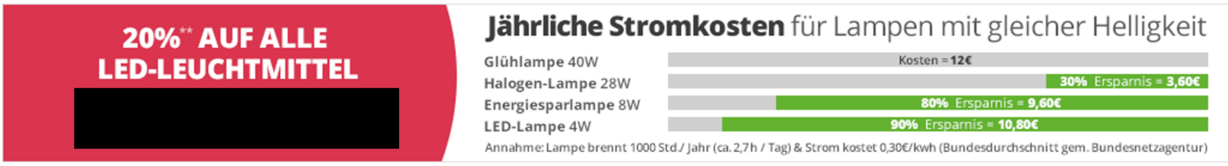


Figure B12: Treatment: More Informative Nudge and Price Discount on CFL Bulbs

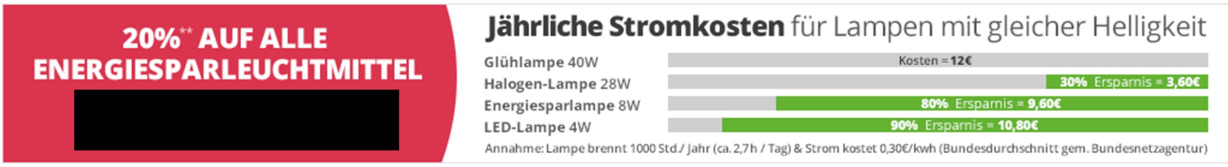


Figure B13: Treatment: More Informative Nudge and Price Discount on Halogen Bulbs

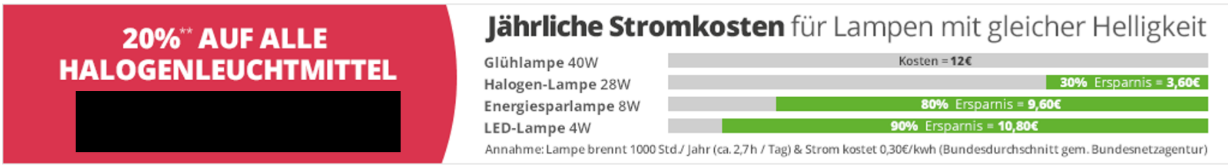


Figure B14: Treatment: More Informative Nudge and Price Discount on Incandescent Bulbs

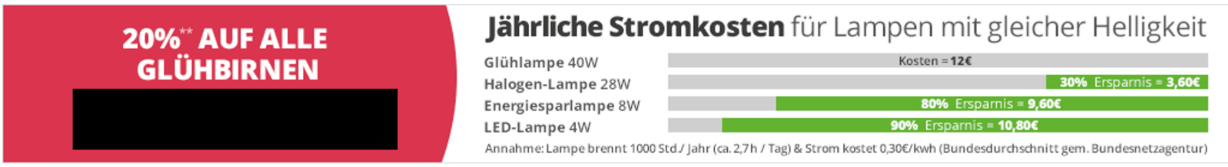
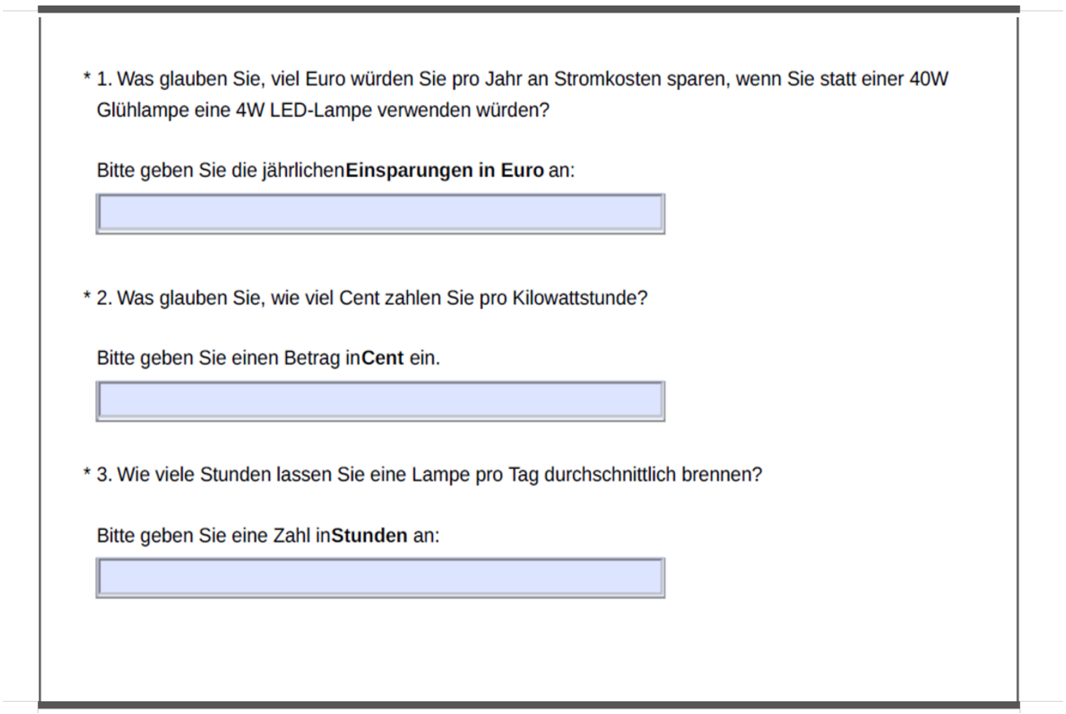


Figure B15: Second Study: Banner Inviting Website Visitors to Participate in the Survey

Figure B16: Placement of Treatments in Webstore

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

Figure B17: Survey to Elicit Beliefs



* 1. Was glauben Sie, viel Euro würden Sie pro Jahr an Stromkosten sparen, wenn Sie statt einer 40W Glühlampe eine 4W LED-Lampe verwenden würden?

Bitte geben Sie die jährlichen**Einsparungen in Euro** an:

* 2. Was glauben Sie, wie viel Cent zahlen Sie pro Kilowattstunde?

Bitte geben Sie einen Betrag in**Cent** ein.

* 3. Wie viele Stunden lassen Sie eine Lampe pro Tag durchschnittlich brennen?

Bitte geben Sie eine Zahl in**Stunden** an:

Note: This figure shows a screenshot of the three questions in German that were asked in the survey.

Table B1: Average Treatment Effects on Purchase Probability

	Probability to purchase
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)
N	640,771
Baseline probability	0.0446

Note: The table shows effects from a linear probability model that regresses the probability to buy at the shop on each of the 14 treatments. The unit of observation is the website visitor. 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 B2: Average Treatment Effects on Demand with Bulk Purchases Included

	(1) LED (most energy efficient)	(2) CFL	(3) Halogen	(4) Incandescent (least energy efficient)
Information Treatments:				
More Informative	-2.645	3.313***	-0.509	0.478
	(5.465)	(1.251)	(2.159)	(1.124)
Less Informative	7.514	0.629	-0.433	2.234*
	(5.484)	(0.731)	(2.225)	(1.315)
Price Discounts:				
LED	16.244***	0.831	0.905	1.390
	(5.639)	(1.012)	(2.532)	(1.283)
CFL	8.300	0.977	2.177	3.934**
	(5.319)	(0.853)	(2.627)	(1.793)
Halogen	-1.444	0.212	4.099*	1.225
	(5.023)	(0.725)	(2.319)	(1.313)
Incandescent	8.009	0.532	1.825	1.567
	(5.495)	(0.629)	(2.391)	(1.213)
Interactions:				
More Informative × LED	-3.579	-3.366**	-0.697	-1.493
	(8.067)	(1.643)	(3.307)	(1.848)
More Informative × CFL	1.260	-3.951**	1.951	-4.252**
	(7.718)	(1.562)	(3.319)	(2.082)
More Informative × Halogen	-0.745	-2.699*	-4.863	-0.382
	(7.514)	(1.500)	(3.331)	(1.627)
More Informative × Incandescent	-4.928	-2.791*	0.458	-1.782
	(7.793)	(1.488)	(3.273)	(1.935)
Less Informative × LED	-10.069	-1.352	1.033	-2.543
	(8.296)	(1.246)	(3.464)	(1.874)
Less Informative × CFL	-10.016	-0.442	-2.896	-6.117***
	(8.089)	(1.207)	(3.352)	(2.111)
Less Informative × Halogen	-6.515	-0.560	-1.996	-2.901
	(7.462)	(1.076)	(3.328)	(1.917)
Less Informative × Incandescent	-15.556**	-0.745	-0.232	-3.712**
	(7.704)	(1.253)	(3.349)	(1.772)
N	31,134	31,134	31,134	31,134
Control group mean	43.515	1.140	7.743	1.710

Note: This table presents results with bulk purchases included. Bulk purchases were defined as the top 1% of light bulb sales.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.