Making energy costs salient can lead to low-efficiency purchases

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Abstract

We conduct a large-scale field experiment with an online retailer to evaluate the impact of energy cost information on purchasing decisions of large household appliances. We vary the presence of energy cost information and its level of aggregation. We find that increasing the salience of energy costs leads to less efficient purchases - especially when providing lifetime energy costs. Search and navigation data on the retailer's website confirm that the treatments increase attention paid to inefficient products. This is consistent with customers over-estimating energy savings from high-efficiency products. Results have implications for designing information campaigns aimed at promoting energy efficiency.

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I. Introduction

Contrary to the assumption that agents fully optimize with respect to all attributes of a good, evidence shows that individuals are inattentive to less salient, non-transparent and complex product attributes (Abaluck and Gruber 2011, 2016; Chetty et al. 2009; Pope 2009). When considering choices with consequences in the future, theories of focusing in decision-making argue that the salience of an attribute is partly driven by its level of aggregation, and that agents undervalue attributes with consequences that are distributed over time relative to those with concentrated advantages (Bordalo et al. 2013; Koszegi and Szeidl 2012). These models and empirical evidence on salience effects imply that increasing the salience of future costs -for instance by displaying them more prominently or transparently, or by aggregating them- will increase the weight given to them by decision-makers.

The energy efficiency of energy-using durables is a prime example of attribute characterized by low transparency, high complexity, and consequences distributed over time. Relative to a product's price, which is typically displayed prominently, is concentrated, and whose consequences are experienced in the present, energy costs are borne in the future, over many small installments, and are typically expressed in terms of annual consumption in kilowatt-hour (kWh). Misperception, lack of information, and limited attention to operating costs are considered as primary contributors to the energy-efficiency gap (Gerarden et al. 2017, 2015; Allcott 2016; Caplin and Dean 2015; Gillingham et al. 2009; Gillingham and Palmer 2014; Allcott and Greenstone 2012).¹ These beliefs underlie calls for policies to make energy cost information more salient and transparent. Labeling schemes emphasizing energy usage and/or associated costs are mandated in several countries in the world, including the US and Europe.

However, the effect of salient and transparent information will depend on agents' underlying beliefs. It is possible that consumers over-estimate energy savings associated with energy efficiency, when only coarse measures of efficiency are available. Indeed, evidence shows that labels influence purchases of energy-using appliances beyond the incentives associated with the actual underlying energy cost (Houde 2018) and that consumers generally over-estimate the benefits associated with energy efficiency certifications, such as Energy Star (Allcott and Sweeney 2017), or with participation in energy-saving programs (White and Sintov 2018). Evidence from other fields confirms that, in the presence of complex or shrouded attributes, agents rely on simplified decision rules, heuristics and labels, rather than more precise information (Lacetera et al. 2012; Chetty et al. 2009). Related evidence on the impact of social comparison on energy consumption shows that its effect depends on agents' prior beliefs about their relative levels of consumption (Byrne et al. 2018).

Empirical evidence of misperception and mis-optimization is pervasive in the energy domain, from underestimation of fuel costs (Allcott 2013; Allcott and Wozny 2014) to incorrect beliefs on the impact of energy conservation behaviors (Attari et al. 2010). The literature on the impact of energy labels relies primarily on choice experiments, and generally finds a positive impact of labels

¹ On the other hand, the pervasiveness of the energy-efficiency gap is questioned (Allcott and Greenstone 2012).

providing energy cost information on preferences for energy efficiency (Hutton and Wilkie 1980; Deutsch 2010b, 2010a; Heinzle 2012; Newell and Siikamäki 2014; Andor et al. 2016). However, providing information on the returns from energy efficiency is found to have limited, and even negative, effects on the efficiency level of actual purchases (Allcott and Taubinsky 2015; Allcott and Sweeney 2016; Allcott and Knittel 2019; Fowlie et al. 2015; Anderson and Claxton 1982; Kallbekken et al. 2013; Carroll et al. 2016; Stadelmann and Schubert 2018; Deutsch 2010b).²

We contribute to this literature by presenting results from a large field experiment conducted with a major Italian online retailer of household appliances. Using data from over 120,000 customers and 7,631 purchases, we compare the impact of experimental treatments providing yearly or lifetime energy cost information to the standard energy consumption information, expressed in kWh per year. We find that information on energy costs results in less efficient purchases, especially when given in aggregate terms. Using data on customers' activity on the retailer's website, we show that the treatments also result in increased attention devoted to the search process, both in terms of number of pages viewed and time spent viewing them. In particular, treatment effects on purchases are mirrored by those on navigation outcomes: treated customers, particularly those provided with lifetime energy cost information, view less efficient products, and spend more time viewing them. We interpret these results as an indication that consumers in our setting overestimate energy savings from energy efficiency, and that energy cost information, by correcting this misperception, helps them evaluate more rationally alternative products. We provide suggestive survey evidence in favor of this explanation. Conditional on consumers overestimating energy prices, our results are consistent with salience and rational inattention theories: our treatments, particularly the one providing lifetime energy costs, increase the salience and ease of processing such attribute, and thus the weigh given to it by decision-makers.

Our study differs from other field experiments on the impact of providing information on the returns from energy efficiency under three respects. First, notable field experiments examine light bulbs, that is, they involve low stakes (Allcott and Taubinsky 2015). Refrigerators are one of the most expensive appliances in terms of price and operating costs: in Italy, refrigerators are responsible for about 15 percent of household energy consumption.³ Moreover, refrigerators' energy consumption is largely independent from usage. Second, we observe the impact of information on the actual choices of marginal consumers. By building our treatments into customers' standard browsing and purchasing experience, we observe choices in a natural setting. Individuals in our sample are not given a shopping budget or other incentives for making purchases, nor are they approached by sales agents or targeted by specific information. Indeed, our treatments do not affect the overall propensity to buy a refrigerator, but shift the choice of products among buyers. The closest studies to ours are Deutsch (2010a, 2010b), who, however, only observes products placed in the cart, not actual purchases. Third, we observe customers' search process. This allows us to shed light on the mechanism behind treatment effects, and confirm that the

² Appendix B features a summary of academic articles on the impact of energy use information on choices of energy-efficient appliances.

³ Enea (Agenzia Nazionale per le Nuove Tecnologie, l'Energia e lo Sviluppo Tecnologico Sostenibile): http://kilowattene.enea.it/KiloWattene-refrigeration-info.html#.

information we provide draws customers' attention. The consistency between the search and purchasing outcomes reinforces the credibility of our results.

II. Experimental design and data

A. Sample

We conducted the field experiment between June 1st and October 16th, 2018, on the website of a major Italian online retailer. Our sample is made of customers who viewed and/or purchased a refrigerator from the desktop version of the website over the duration of the study. For each customer, we have the full navigation history, consisting of one observation per page viewed.

We identify customers primarily through their registration ID, which must be entered in order to make a purchase, but not to navigate pages. Cookie-based identification codes, linked to the computer's IP address and browser, identify customers who are not logged-in. We assign to the same registered customer ID all observations with the same cookie-based ID and missing registration ID: these are pages that a registered user viewed without being logged-in. We identify the remaining customers, i.e., customers who never register or log-in, through their cookie-based ID. This may leave room for two main types of errors: first, we may assign different IDs to the same customer, if she never logged-in and erased the cookies or used different browsers or computers; second, we may assign the same ID to different customers if they never logged-in and used the same shared computer and browser. We do not have reasons to think, however, that these cases may occur at differentially across treatments. This procedure leads to a sample of 128,206 customers who viewed a refrigerator page over the study period.

Assignment to treatment was performed by a cookie-based software routinely used by the online retailer for AB tests. Each customer, visiting the retailer's website for the first time during the study period, was randomly assigned to one of three treatments, described below. Therefore, as long as a customer did not erase the cookies, she would be exposed to the same treatment on all her subsequent visits. Moreover, once a treatment was associated to a customer ID, it was also displayed on other devices or web browsers used by the customer, if she was logged-in when starting to browse refrigerator pages. This, however, implies that the same customer could be exposed to multiple treatments, if she viewed refrigerators from different computers or laptops without being registered or logged on. This should attenuate any treatment effect we detect, but otherwise should not represent a threat to the identification, since the occurrence of such cases should be orthogonal to treatment. Indeed, 7,243 customers in our sample were assigned to multiple treatments; of them, 1,313 made a purchase. In the analysis, we assign these customers to the modal treatment and test the robustness of our results to their exclusion from the sample.

We observe 7,631 single purchases of refrigerators over the study period. For customers who made multiple purchases (n = 290), we keep only the latest one, so that we have at most one refrigerator purchase per user.⁴ We test the robustness of our results to the exclusion of customers who make

⁴ Multiple purchases are predominantly cases of orders canceled and then re-issued, for instance, following a payment failure due to insufficient funds on a pre-paid card.

multiple purchases. Ruling out multiple treatments and multiple orders results in a sample of 120,779 users and 6,137 purchases.

B. Experimental design

Customers viewing the website refrigerator pages during the study period were randomly assigned to one of three conditions: (a) the 1-year condition provided information on the yearly energy usage cost of each product; (b) the 15-years condition provided information on the lifetime energy usage cost of each product; and (c) the control condition presented the retailer's default product visualization, with no information on energy usage costs.

The energy cost information was provided through a sentence placed next to an icon reproducing the energy class symbol contained in the energy label. This icon was also present in the control condition. It was aimed at helping customers understand that the information referred to energy costs and reminding them of the energy class of the product. The sentence reported the energy usage cost in Euro as "You spend X Euro for energy in 1 year/15 years", depending on the treatment. We provided the energy cost information in two places on the website: (a) on product listing pages, where products are displayed in a list: here, the information on a specific product appeared when the customer hovered the mouse over it; and (b) on product pages, where a single product is displayed in detail: here, the information was placed just below the product image. In addition, each time the customer clicked on the cost information sentence, a pop-up window explained the nature of the information and the sources of data for the kWh unit cost and refrigerator lifetime. Online Appendix A provides screenshots from the retailer's website of listing and product pages (Figures A1 and A2), and pop-up message (Figure A3), by condition.

The energy cost was calculated by multiplying the yearly energy consumption in kWh, as reported on the product's energy label, by the average unit cost of a kWh, taken from the website of the Italian Authority for Energy, Gas and Water (ARERA).⁵ We selected the latest available figure of the residential cost of a kWh, equal to 0.1998 Euro in the second quarter of 2018, and computed all energy usage costs applying this same unit cost, undiscounted, to all future periods. The average lifetime of a refrigerator was set at 15 years, based on estimates available from the website of the National Agency for new technologies, energy and sustainable development (Enea).⁶ When computing lifetime energy costs, we simply multiplied yearly costs by average lifetime: while not discounting lifetime energy costs arguably inflates them, we opted to present undiscounted figures to maximize the transparency and simplicity, and thus the credibility, of the information and to avoid imposing a single exogenous discount rate to future costs experienced by a wide range of individuals. Interested customers in the treatment groups could verify the data, on which the energy cost calculation was based, by clicking on the links provided in the pop-up window.

The product categories included in the study are free-standing refrigerators (except minibars) available for delivery during the time of the study, so built-in or out-of-stock refrigerators were

⁵ The information was taken from the following page: https://www.arera.it/it/dati/eep35.htm.

⁶ The website reports results from a series of engineering studies evaluating the average lifetime of a refrigerator: http://kilowattene.enea.it/KiloWattene-refrigeration-info.html.

excluded from the RCT. These criteria were met by about 2000 products on the online retailer's catalog.

C. Data

The analysis relies on the combination of different datasets. The main source of data consists of navigation data, extracted daily from the online retailer. The dataset contains one observation per page visited by users, for all users who visited any page of the retailers' website between June 1st and October 16th, 2018. The raw data contain information on the municipality of the user's IP address, details on the page visited, whether the internal search engine was used and the search query, the time of the page visit and the number of seconds spent viewing the page. If the page viewed by the customer is a product or cart page, then the data also report the product code and whether the product was added to the cart, to the favorites, or ordered.

We collapse the raw data at the user level, creating variables for both purchase and navigation outcomes. As for purchases, we record their characteristics, among which energy class, consumption in kWh, and price. In terms of navigation, the dataset contains information on the total number of refrigerator pages viewed, the total time spent on them in seconds, the number of refrigerators' product pages viewed, the number of refrigerators added to the cart and to the favorites, overall and by product's energy class. For each user, we also record the modal treatment she was exposed to and the number of other (non-refrigerator) orders she placed. Online Appendix Table A1 reports summary statistics of available baseline customers' characteristics and shows that they are balanced across treatments. Based on IP addresses, users come from all over the country, with the largest shares from North-Western and central Italy. With respect to national averages, our sample is drawn from municipalities with somewhat higher shares of high school or university graduates, and slightly higher income levels. 8

The second set of data comes from the product catalog, and contains information on refrigerators. For each product, identified by the product code, the data reports a description of the product, its brand, category (e.g., one door, fridge-freezer, three doors, etc.), energy class, yearly consumption in kWh, and the corresponding yearly and lifetime energy costs in Euro. The majority of products (50.8 percent) is in the A+ energy class, followed by A++ (38 percent) and A+++ or above (9.5 percent). On average, refrigerators consume 266 kWh of electricity yearly, equivalent to 53 Euro, or 798 Euro over 15 years. Average lifetime energy cost by energy class of the refrigerators included in the retailer's catalog is smallest for most efficient products and highest for least efficient ones, ranging between 496 Euro for A+++ or above refrigerators, 750 Euro for A++ and 905 Euro for A+ or below ones.⁹

⁷ When collapsing the page-level dataset at the individual level, we correct for multiple observations. Multiple observations occur primarily when customers view their cart, if it contains multiple products. Namely, if the cart contains N products, the dataset features N rows anytime the user views it, one for each product. In these cases, we assign to each row a value of 1/N and a time spent on the page equal to the total seconds spent on the cart page divided by N.

⁸ Comparison made with the dataset of municipalities from Guiso et al. (2016).

⁹ At the time of the study, two additional energy classes were available: A+++ minus 10% and A+++ minus 20%, respectively 10 and 20 percent more efficient than the average A+++ refrigerator. The catalog also includes

The third dataset contains daily price information for each refrigerator that was viewed on the website during the time of the study. That is, for each product viewed, we have the price applied to the product each day from June 1st to October 16th, plus its shipping price and information on any active promotion on the product on that date. Refrigerators cost, on average, 660 Euro, and price is increasing with energy efficiency: refrigerators of energy class A+++ or above cost, on average, almost 300 Euro, or 56 percent, more than products of energy class A+ or below (Online Appendix Table A2). Prices are determined by three main factors. First, availability of a product in stock: since the online retailer sells own products and products supplied by other sellers, the product price is the lowest one among those of suppliers with the product available in stock. Second, competitors' prices: for its own products, the online retailer uses an algorithm to automatically match the price charged by competitors for the same product, which leads to multiple price updates within each day. Third, offers are activated on the basis of a product's category or state: for instance, offers on air conditioners are launched when temperatures rise in late spring; and products returned by customers in good conditions are typically placed on sale. As a result, prices vary greatly within each week: the average difference between the maximum and minimum price for the same product within a week is about 13 percent of the average price, corresponding to 107 Euro for A+++ refrigerators and 71 Euro for A+ ones. 10

Finally, we have municipal-level data on population, income, education, and other socioeconomic characteristics from Guiso et al. (2016), which we match to the municipality of the user's IP address. In the case of multiple municipalities per user, we consider the modal one. We are able to match the retailer's data with the municipality data for 123,022 users. In the analysis, we do not drop customers for whom we have no municipal level information, but code them as coming from an 'unknown' municipality.

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refrigerators of class A, although they could not be sold by law. Given the low frequency of these instances (less than 0.5 percent overall), we pool them with A+++ and A+ products, respectively.

¹⁰ Online Appendix Figure A4 displays such price variation, by energy class, over the study period.

III. Results

A. Overview of users' behavior

Out of the 128,206 users in our sample, 43,630 were assigned to the control treatment, 42,654 to the 1-year energy cost treatment, and 41,922 to the 15-years energy cost treatment. About 19.74 percent of users (25,304) registered or logged-in to the website at some point. On average, users viewed 10.1 refrigerators' pages, ranging between 8.1 for those who did not make a purchase and 42.1 for those who did. This corresponds to an average 734 seconds spent browsing refrigerators, 3,057 (about 51 minutes) among buyers and 587 (9.8 minutes) among non-buyers. Buyers added, on average, 1.43 products to the cart and 0.2 to the favorites, and only 1.7 percent of them (0.7 percent overall) clicked on the energy cost information to learn more.

Of the 7,631 purchases of refrigerators made over the study period, 2,631 are in the control, 2,572 in the 1-year and 2,428 in the 15-years treatments. This corresponds to an overall conversion rate of 5.95 percent. Of these purchases, 39.94 percent were of refrigerators of energy class A+ or below, 42.35 percent of class A++, and 17.71 percent of energy class A+++ or above. On average, purchased refrigerators cost 565 Euro, about 100 Euro, or 14.4 percent, less than the average refrigerator viewed on the website and included in the retailer's catalog.

Figure 1 compares the total cost, broken down into price and lifetime energy cost, of products on the retailer's catalog, of viewed products and of purchases. The figure shows how the difference in total cost by class changes when moving from products in the catalog dataset, where each product is observed once (Panel A); to products viewed on the retailer's website, where each product is observed as many times as it is viewed on the website (Panel B); to purchased products, where each product is observed as many times as it is bought by users (Panel C). The average price of products decreases across all energy classes when moving from catalog to views, and even more so when going from views to purchases. Indeed, users pay attention to prices when deciding what to buy, preferring cheaper products or products on offer. 13 On the other hand, users do not seem to take energy costs into much consideration when making their purchase decisions. Energy costs do not decrease on average from catalog to purchases: while they decrease, by 78 Euro, or 8 percent, for refrigerators of energy class A+ or below, they increase by 45 Euro, or almost 10 percent, for those of energy class A+++ or above. Moreover, while energy costs of A++ refrigerators are, on average, lower than those of A+ ones when considering the full catalog, they are almost indistinguishable (812 Euro versus 808 Euro) when considering the sample of purchases. Overall, among purchases, the average total cost is roughly the same for class A+++ or above and class A+ or below refrigerators, 1,260 and 1,220 Euro respectively, while it is higher, equal to 1466 Euro, for A++ products. We elaborate more on the trade-off between prices and energy costs in the next sub-section.

¹¹ We observe 19 purchases of refrigerators of class A, and 4 purchases in each of the A+++ -10% and A+++ -20% classes.

¹² Online Appendix Table A3 provides summary statistics of users' behavior.

¹³ Price discounts were applied on 15 percent of purchased products, while 60 percent of purchased products benefited from free delivery.

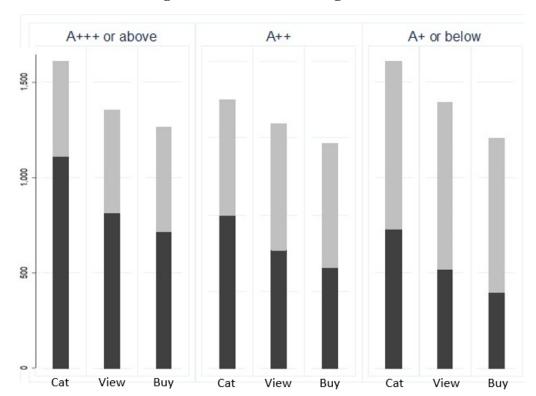


Figure 1. Total cost of refrigerators

Note: The vertical axis expresses costs in Euro. Total cost is defined as the sum of the price (dark grey) and the 15-years energy cost (light grey). Each panel considers one energy class: A+++ or above (left panel), A++ (middle panel), A+ or below (right panel). Within each panel, the left bar (Cat) considers catalog data: one observation per product; the middle bar (View) considers navigation data: one observation per visualization; and the right bar (Buy) considers purchase data: one observation per purchase.

B. Treatment effects on purchase decisions

We evaluate the direct impact of making energy costs more salient and transparent, and the differential direct impact of changing the level of aggregation of the energy cost information, on the likelihood of making a purchase and on the characteristics of refrigerators bought. We address these questions by estimating the following regression model, with robust standard errors:

$$y_{itm} = \beta_1 + \beta_2 Treat_i + \beta_3 PriceA3_t + \beta_4 PriceA2_t + \beta_5 PriceA1_t + \gamma_t + \delta_m + \varepsilon_{it}$$
 (1)

Where y_{itm} is an outcome for customer i, who visited the website refrigerator pages for the first time at time t and navigated the website primarily from municipality m; $PriceA3_t$, $PriceA2_t$ and $PriceA1_t$ are, respectively, the average price of refrigerators of class A+++ or above, A++, and A+ or below on date t, divided by 100; γ_t are time fixed-effects indicating the week, within which day t falls; and δ_m are municipality fixed-effects. $Treat_i$ is treatment status: we first compare treated and control customers, and then distinguish between the 1-year and the 15-years energy cost treatments. When we study the decision to purchase a refrigerator, the sample includes all customers who browsed refrigerator pages, regardless of whether they registered to the website or

bought a refrigerator. When analyzing the characteristics of products bought, our preferred specifications instead focus on the sub-sample of customers making a purchase.¹⁴ We use linear regression models, except when the dependent variable is the refrigerator's energy class - coded by assigning higher values to less efficient energy classes - in which case we adopt an ordered probit model.

Table 1 reports the impact of being treated (Panel A), and of each treatment separately (Panel B). Being treated has no effect on the overall likelihood that a customer buys a refrigerator (Column 1). This result holds even when we distinguish between the two treatments. This is reassuring, as it implies that the treatments did not introduce systematic selection in the sample of customers who made purchases, by attracting or driving them away from the website. Moreover, this implies that our results on the features of purchased products capture treatment effect on marginal customers, i.e., customers who would have bought a refrigerator anyway, but whose choice between different products was shifted by the information we provided.

Next, we examine the impact of being treated, and of individual treatments, on the features of purchases. Treated customers buy refrigerators in less efficient energy classes (Column 2): this result, based on an ordered probit regression assigning higher values of the dependent variable to less efficient energy classes, is our preferred specification, as it better deals with the issue of multiple hypotheses testing. However, we also provide results of separate regressions by energy class, showing that customers buy fewer of the most efficient products and more of the least efficient ones (Columns 3-5). The ordered probit results show that treated customers are 1.7 percentage points less likely to buy an A+++ refrigerator, and 2.5 percentage points more likely to buy an A+ refrigerator (p = 0.018). Focusing on the regressions on purchases by energy class, the treatment effect on the likelihood of purchasing an A+++ refrigerator is significant at the 5 percent level.

Breaking these effects down by treatment, we see that they are driven by the 15-years treatment. Specifically, in the ordered probit regression the 1-year treatment decreases the likelihood that a customer buys an A+++ or an A++ refrigerator by 1.2 and 0.5 percentage points, respectively, while it increases the likelihood of purchases in the lowest energy class by 1.7 percentage points, but these results fall short of conventional statistical significance (p = 0.153). On the contrary, the effects of the 15-years treatment – a reduction by 2.2 and 1 percentage points in the likelihood of purchases in top two energy classes, respectively, and an increase by 3.3 percentage points in the probability of purchases of A+ refrigerators- are both larger in magnitude and statistically

not know that we could exploit daily variations in prices in the analysis.

¹⁴ This study is registered in the AEA RCT Registry (AEARCTR-0003939). The registered pre-analysis plan (PAP) was written before having access to the full set of cleaned data. The PAP analysis is reported in Online Appendix C: its results are consistent with those presented in the main text. The specifications presented here depart from the PAP for the inclusion of the price controls and the consequent replacement of day-fixed effects with week fixed-effects. Including price controls is important. They are absent from the PAP because, at the time of writing it, we did

¹⁵ In the PAP, we proposed to deal with the correlation between the outcome variables in regressions of treatment effects on the energy class of purchases by using SUR. Online Appendix Table C2 reports the regression results.

significant (p < 0.007). Regressions by energy class show that the 15-years treatment increases the share of least efficient purchases by 9.1 percent, or 3.6 percentage points (p < 0.05). 16

In terms of treatment effects on other product characteristics, we find, in line with the effects on the energy class of purchases, that treated subjects tend to buy refrigerators with higher energy consumption, although only the effect of the 15-years treatment is significant at the 10 percent level (Column 6).¹⁷ As mentioned above, more efficient products tend to have other desirable characteristics, and thus be more expensive on average. Consistent with the observed effects of the treatments on energy class, and with the presence of a positive correlation between efficiency and price, treated customers buy cheaper refrigerators (Column 7): this effect is small, a reduction of 18.5 Euro, or 3.3 percent, among treated buyers, and statistically significant at the 5 percent level overall and at the 10 percent level for the 15-years treatment.¹⁸ Given that the treatments lead customers to buy refrigerators with lower prices, but higher energy costs, we examine the effect of the energy cost information on the total cost of purchased refrigerators, computed as the sum of sale price and lifetime (i.e., 15-years) energy cost (Column 8). Treated customers buy products with lower total cost, on average, but this effect is not statistically significant.¹⁹

We have seen that the 15-years treatment generates larger and statistically significant effects, with respect to the control condition. However, the effects of the two treatments are generally not significantly different from each other, with few exceptions. Namely, the 15-years treatment has a significantly larger impact than the 1-year one only on the likelihood that customers buy an A+ refrigerator, and on the energy consumption of purchases (both p < 0.1).

Prices are correlated with purchases as expected: the likelihood of purchasing a product in a certain energy class depends negatively on the price of products in the same energy class, and positively on the price of products in other energy classes. Specifically, buyers appear to substitute products in higher energy classes (A+++ or above and A++) with A+ or below products, while they do not seem to switch between A+++ or above and A++ products as their relative prices change. This pattern parallels the one determined by our treatments. Comparing the coefficients on the price variables, capturing the effect of a 100 Euro increase in prices, to the treatment coefficients indicates that the impact of information on energy costs is large and economically meaningful: for instance, the effect of being treated on the likelihood that a customer buys an A+++ refrigerator is about half that of a 100 Euro increase in their price, while the 15-years treatment has about one-third of the effect of a 100 Euro increase in own price on purchases of A+ refrigerators. Both treatment effects are roughly equivalent to the impact of a 6 percent increase in price.

¹⁶ Online Appendix Figure A5 displays the average shares of refrigerator purchases, by energy class and treatment.

¹⁷ The results are robust to considering the full sample of users; and to excluding buyers exposed to multiple treatments, or who made multiple purchases (Online Appendix Table A4).

¹⁸ Sale price information is not available for 90 refrigerators, which explains the drop in the number of observations in Columns 5 to 8 of Table 6.

¹⁹ Treated customers do not buy smaller refrigerators, measured by capacity in liters (result available upon request). While we would like to test whether the treatments affect the quality of purchases, the available data do not allow this type of analysis: we have information on products' brands and models, but a mapping from these features to quality is not available.

After establishing that both experimental treatments lead to a shift in the efficiency level of customers' purchases, we exploit the daily variation in prices and the detailed information available on customers' navigation history to estimate the implied discount rate. The estimation framework is analogous to the attention weight models in Allcott and Wozny (2014), Newell and Siikamaki (2015), Chetty et al. (2009) and Della Vigna (2009). Namely, we estimate the relative weight given to the price and energy cost by regressing them on purchase decisions. This analysis makes use of the full navigation data for buyers, with observations at the level of individual, product code and price: each product that a buyer views is included in the dataset as many times as the number of different prices attached to it, viewed by the buyer during her navigation on the website. We focus on treated customers for this analysis, assuming that they are fully informed of the energy costs and take this information into account when making their purchasing decision. We do not differentiate the two treatments due to the general lack of statistically significant differences between the 1-year and 15-years treatment effects. By computing the ratio of the decision weights given to the price and energy costs, derived from the regression coefficients, we obtain an estimate of the decision weight attached to 1 Euro of annual energy cost equal to 4.72 or 4.34, depending on the model, when normalizing the decision weight attached to 1 Euro of purchasing price to 1. With our assumption of full attention and complete information in treatments, the decision weight translates to an implied discount rate equal to 18 percent or 19.8 percent. This is very close to the elicitation in Newell and Siikamaki (2015) of 19 percent on average. Online Appendix D provides further details of the estimation theoretical framework, assumptions and results.

Table 1. Treatment effects on purchase decisions

Sample	All				Buyers		-			
Dependent variable		Feature of refrigerator bought								
	Buys a	Energy class	A+++ or above	A ++	A+ or below	Energy consumption (kWh)	Price	Total cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
Panel A	` /			/						
Treat	-0.001	0.074	-0.022	0.000	0.022	1.890	-18.564	-11.422		
	(0.001)	(0.031)	(0.011)	(0.014)	(0.013)	(2.050)	(8.973)	(12.794)		
Avg. Daily price A+++ or above	-0.006	0.135	-0.042	0.007	0.034	0.250	-9.596	-10.142		
	(0.002)	(0.041)	(0.013)	(0.017)	(0.018)	(2.636)	(11.529)	(16.438)		
Avg. Daily price A++	-0.008	0.091	0.007	-0.071	0.056	2.158	32.351	41.527		
	(0.002)	(0.049)	(0.017)	(0.021)	(0.021)	(3.214)	(14.065)	(20.053)		
Avg. Daily price A+ or below	0.004	-0.262	0.051	0.057	-0.102	8.978	60.524	87.401		
	(0.003)	(0.062)	(0.021)	(0.027)	(0.027)	(4.016)	(17.570)	(25.050)		
Mean of dep var	0.060	2.223	0.175	0.418	0.395	252.409	565.053	1322.165		
Number of Obs	128167	7533	7631	7631	7631	7631	7541	7541		
R-Squared	0.029		0.145	0.175	0.181	0.184	0.220	0.211		
Panel B										
Treat 1 year	0.000	0.051	-0.021	0.011	0.009	-0.356	-17.475	-17.323		
	(0.002)	(0.036)	(0.012)	(0.016)	(0.015)	(2.364)	(10.347)	(14.751)		
Treat 15 years	-0.002	0.098	-0.022	-0.012	0.036	4.273	-19.722	-5.145		
	(0.002)	(0.037)	(0.013)	(0.016)	(0.016)	(2.400)	(10.514)	(14.989)		
Avg. Daily price A+++ or above	-0.006	0.135	-0.042	0.007	0.034	0.213	-9.578	-10.236		
	(0.002)	(0.041)	(0.013)	(0.017)	(0.018)	(2.635)	(11.530)	(16.438)		
Avg. Daily price A++	-0.008	0.091	0.007	-0.071	0.056	2.161	32.353	41.513		
	(0.002)	(0.049)	(0.017)	(0.021)	(0.021)	(3.214)	(14.066)	(20.053)		
Avg. Daily price A+ or below	0.004	-0.261	0.051	0.057	-0.102	9.068	60.486	87.609		
	(0.003)	(0.062)	(0.021)	(0.027)	(0.027)	(4.016)	(17.572)	(25.052)		
Mean of dep var	0.060	2.223	0.175	0.418	0.395	252.409	565.053	1322.165		
Number of Obs	128167	7533	7631	7631	7631	7631	7541	7541		
R-Squared	0.029		0.145	0.175	0.181	0.184	0.220	0.211		
p-value for test: treat 1 yr = treat										
15 yrs	0.120	0.205	0.919	0.156	0.093	0.055	0.832	0.421		
Week f.e	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Municipality f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		

Note: OLS regressions in all columns, except Column 2 (Ordered probit). Robust standard errors in parentheses. All regressions control for week and municipality fixed-effects.

C. Treatment effect on search patterns

The results on purchases indicate that providing information on energy costs affected customers' choice of products. We exploit available data on the pages viewed by customers to study whether these different choices result from different search patterns induced by the treatments. The outcome variables in this analysis are the number of refrigerators' product pages viewed and the time spent navigating them.

While we observe no treatment effects on overall search outcomes, in terms of overall number of pages viewed or the time spent on them by users (Online Appendix Table A4), we find that the energy cost information deepens the search process among buyers, in terms of both alternatives considered and time spent examining them (Table 2). Treated customers view 2.2 more refrigerators' pages and spend 188 more seconds searching, an increase of 5.2 (p < 0.1) and 6.2 percent (p < 0.05) over the mean of the dependent variable, respectively. Along both dimensions, the result is driven by the 15-years treatment, with treatment effects significant at the 1 percent level for search time.

Disentangling these effects by energy class, we see that the increase in overall search depth and time is concentrated among products in lower energy classes. Treated subjects view an extra 0.04 pages of products in classes A+ or below relative to control ones; and spend 102 and 98 seconds more on products in classes A++ and A+ or below, respectively. This corresponds to a 7.7 (p < 0.1) and 9.4 percent (p< 0.05) increase in time spent viewing refrigerators of energy class A++ and A+ or below, respectively. As in the analysis of purchase decisions, these results are driven by the 15-years treatment, which leads to an 11.9 (p < 0.05) and 13.4 (p < 0.01) percent increase in products viewed and search time, respectively.

Product prices do not appear to determine the choice of which products to view, but do affect the time spent viewing products in different energy classes, with a pattern consistent with the one observed for product purchases.

Overall, the analysis of purchase and navigation outcomes paints a consistent picture: providing information on the energy cost of products increases the attention given by prospective buyers to lower efficiency products and the likelihood that these users eventually purchase such items.

Table 2. Treatment effect on search outcomes: buyers

Dependent variable	Nun	nber of refrige	rator pages vi	ewed	Number of seconds spent on refrigerators' pages			
_		A+++ or				A+++ or		
_	All	more	A++	A+ or less	All	more	A++	A+ or less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Treat	2.217	0.000	-0.010	0.036	188.334	-24.028	102.237	97.908
	(1.173)	(0.002)	(0.008)	(0.018)	(88.235)	(44.618)	(60.622)	(45.627)
Avg. Daily price A+++ or above	1.302	0.000	-0.001	-0.045	-64.320	-76.072	-8.278	44.092
	(1.449)	(0.001)	(0.005)	(0.028)	(103.570)	(52.523)	(69.586)	(55.723)
Avg. Daily price A++	-1.444	0.004	0.008	0.061	-117.206	36.068	-143.195	-24.167
	(1.943)	(0.003)	(0.007)	(0.048)	(142.291)	(72.969)	(93.698)	(77.596)
Avg. Daily price A+ or below	-0.248	0.000	-0.000	-0.072	36.778	156.217	-12.815	-96.650
	(2.259)	(0.003)	(0.010)	(0.047)	(177.988)	(84.909)	(120.565)	(96.118)
Mean of dep var	41.956	0.003	0.012	0.068	3037.892	582.905	1323.610	1043.708
Number of Obs	7631	7631	7631	7631	7631	7631	7631	7631
R-Squared	0.158	0.317	0.175	0.235	0.183	0.202	0.151	0.160
Panel B								
Treat 1 year	1.370	-0.000	-0.011	0.036	96.047	-25.161	50.410	58.043
	(1.319)	(0.002)	(0.007)	(0.023)	(99.911)	(51.013)	(68.278)	(53.841)
Treat 15 years	3.116	0.001	-0.009	0.036	286.191	-22.827	157.193	140.179
	(1.469)	(0.002)	(0.010)	(0.027)	(110.587)	(53.312)	(75.810)	(54.526)
Avg. Daily price A+++ or above	1.288	0.000	-0.001	-0.045	-65.826	-76.091	-9.123	43.441
	(1.449)	(0.001)	(0.005)	(0.028)	(103.541)	(52.462)	(69.622)	(55.656)
Avg. Daily price A++	-1.443	0.004	0.008	0.061	-117.102	36.069	-143.137	-24.122
	(1.943)	(0.003)	(0.007)	(0.048)	(142.269)	(72.972)	(93.725)	(77.585)
Avg. Daily price A+ or below	-0.215	0.000	-0.000	-0.072	40.470	156.262	-10.741	-95.055
	(2.257)	(0.003)	(0.010)	(0.047)	(177.823)	(84.841)	(120.359)	(96.259)
Mean of dep var	41.956	0.003	0.012	0.068	3037.892	582.905	1323.610	1043.708
Number of Obs	7631	7631	7631	7631	7631	7631	7631	7631
R-Squared	0.158	0.317	0.175	0.235	0.183	0.202	0.151	0.160
p-value for test: treat 1 yr = treat								
15 yrs	0.209	0.604	0.803	0.974	0.070	0.963	0.140	0.127
Week f.e	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regressions in all columns. Robust standard errors in parentheses. All regressions control for week and municipality fixed-effects.

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²⁰ Online Appendix Table A5 shows that the results are robust to alternative definitions of the sample.

IV. Discussion

Our analysis shows that providing information on the energy costs of energy-using appliances results in less efficient purchases. Providing information in terms of lifetime, rather than yearly, energy costs produces larger effects, and significantly different from those of standard energy consumption information, but the difference in the impacts between the two levels of aggregation is generally not statistically significant. The information allows customers to more easily compute the total cost of products, defined as price plus lifetime energy costs, and buy refrigerators belonging to the energy class with the lowest total cost. The magnitude of these information effects is large, equivalent to those of price increases of about 6 percent. The fact that these effects on decisions are accompanied by increases in search time indicates that the treatments encourage users to make more pondered decisions.

The treatment effects that we find are of the opposite sign, with respect to the existing evidence on the impact of energy labels and energy cost information from choice experiments and field experiments on smaller energy using durables. Our results suggest that customers in our setting overestimate the energy savings from efficient products when only information on energy consumption is available. Support for this explanation comes from a survey of a representative sample of 1500 customers of a major Italian energy utility, conducted by two of the authors of the present study, and discussed in Bonan et al. (2019). The survey asked respondents to estimate the price of a kWh: the average answer was 0.37 Euro, almost twice as much as the actual price (0.20 Euro) used in computing energy costs in the present study. This corresponds to an overestimation of yearly energy costs of the average refrigerator by 45 Euro, or by 669 Euro in terms of lifetime energy costs. The magnitude of such overestimation is, of course, increasing in a product's energy consumption. This argument is also consistent with existing evidence, showing how consumers rely on and value energy labels beyond the energy savings associated with them (Houde 2018) and overestimate the energy savings associated with higher energy efficiency standards (Allcott and Sweeney 2017).

Our results demonstrate that making energy costs salient and transparent is not by itself conducive to more efficient decisions, when energy costs are low. Policymakers wishing to foster investment in energy efficiency should consider providing information on co-benefits from energy savings, such as positive environmental and health impacts (Asensio and Delmas 2015). A more straightforward policy to increase energy efficiency is increasing energy prices: pricing the carbon associated with the climate externality would results in higher electricity costs, making energy-efficient products more attractive. Our study shows that information provision does affect energy usage decisions. With the diffusion of energy and climate policies around the world, information provision has an important role to play to help citizens decide how to invest in a low-carbon world.

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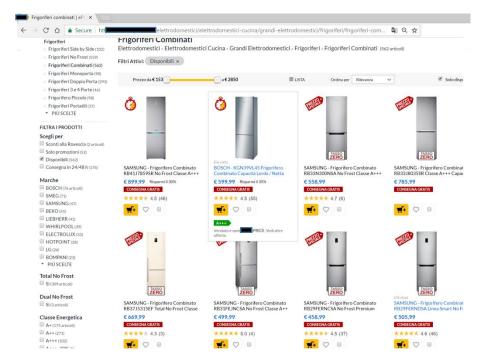
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Online Appendix

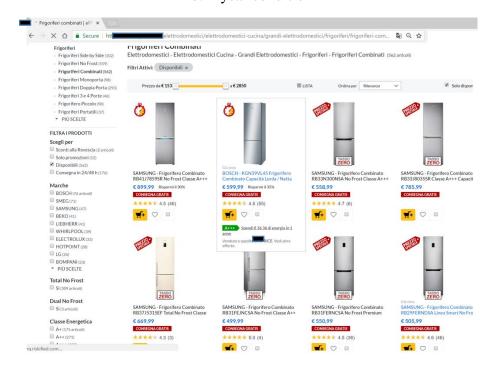
Appendix A: Table and Figures

Figure A1. Listing page

a. Control



b. 1-year condition



c. 15-year Condition

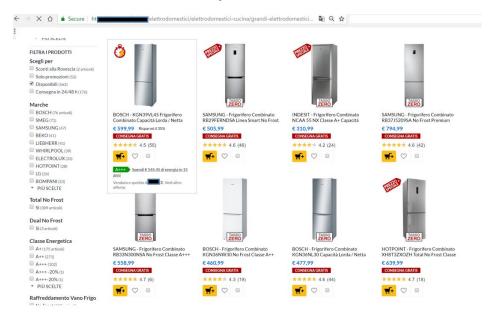
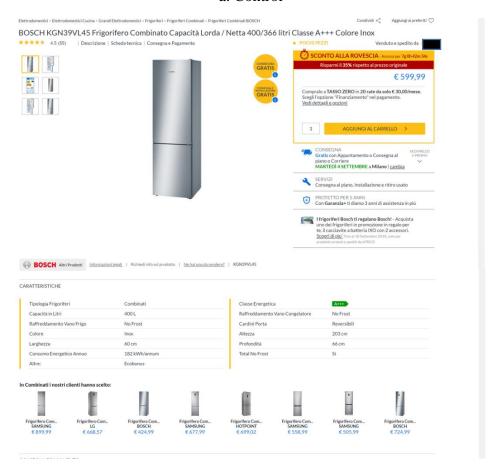


Figure A2. Product page

a. Control



b. 1-year condition



c. 15-year condition



Figure A3. Pop-up

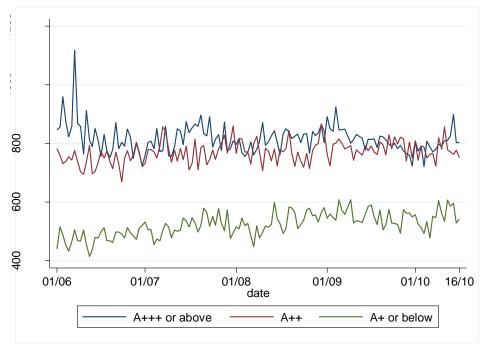
a. 1-year condition

Costo del consumo di energia elettrica del prodotto Il consumo energetico annuo del prodotto è contenuto nell'etichetta energetica, ed è valorizzato sulla base del prezzo del kWh per una famiglia tipo (contratto di maggiori trelac, consumi muni di 2.700 kWh o per una famiglia tipo (contratto di maggiori trelac, consumi muni di 2.700 kWh o per una famiglia tipo (contratto di maggiori trelac, consumi muni di 2.700 kWh, pari a 0.1998€ (fronte dati AREA, secondo trimetre 2018²). La vita media di un frigorifero è stimata pari a 15 anni (fronte: ENEA³). Con questo prodotto classe A+++ in 1 anno spendi € 36,36 CHIUDIE PROSEGUI CON GLI ACQUISTI In collaborazione con il progetto COBHAM del Politecnico di Milano ⁴ 2 son AREA 3 son EREA 4 like gest agressoret ₹ 30515 - pregetto COBIAM The role of consumer behaviora and heterogeneily in the listaggiated assessment of energy and distincte projectio.

b. 15-year condition



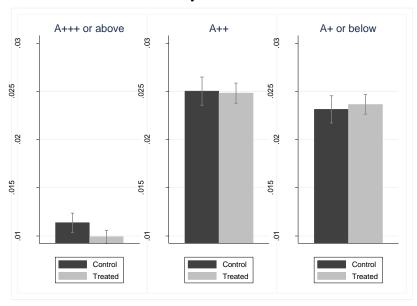
Figure A4. Variation in prices over the study period



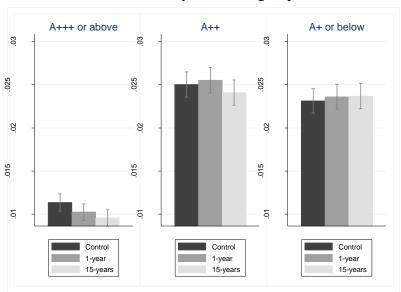
Note: The vertical axis expresses prices in Euro. Average daily prices are defined as the average price of products viewed on each day.

Figure A5. Share of refrigerator purchases, by energy class and treatment

Panel A. By treatment status



Panel B. By treatment group



Note: Bars denote means, whiskers 95% confidence intervals.

Table A1. Price of refrigerators

	Mean (sd)
Avg. daily price	660.04
	(29.83)
Avg. Daily price A+++ or above	815.66
	(48.61)
Avg. Daily price A++	770.34
	(37.07)
Avg. Daily price A+ or below	522.57
	(40.85)
Weekly variation in price A+++ or above	107.24
	(65.16)
Weekly variation in price A++	87.40
	(29.29)
Weekly variation in price A+ or below	71.22
N	(16.45)

Note: all values are expressed in Euro. Standard deviations in parentheses. Average daily prices are defined as the average price of products viewed on each day. Averages displayed in the table are computed over the study period (June 1st-Oct 16th).

Table A2. Summary statistics of users' characteristics and balance test

	Mean	p-value
	(1)	(2)
User placed another (non-refrigerator) order	0.0441	0.6745
Number of other (non-refrigerator) orders placed	0.0734	0.8980
User ordered more than one refrigerator	0.0400	0.2714
Municipality's population (/10000)	0.6766	0.3838
North East	0.0933	0.6438
North West	0.3919	0.8237
Center	0.2885	0.1777
South	0.1329	0.1882
Islands	0.0627	0.3694
Municipality's per capita income (Euro)	12,919	0.1799
Frequency of municipality's population with high school diploma	0.2877	0.6076
Frequency of municipality's population with undergraduate degree	0.1107	0.6019
Frequency of municipality's population in the labor force	0.4978	0.1308
Frequency of municipality's labor force employed	0.4495	0.1982

Note: Column 2 reports the p-value of a joint test of the null hypothesis that beta(15-years treatment) = beta(1year treatment) = 0, from a regression of users' characteristics on treatment dummies and date fixed-effects. Regressing treatment status on the full set of individual traits yields an F-statistics of joint significance of the regressors equal to 1.12, thus indicating a low predictive power of covariates for treatment status.

Table A3. Summary statistics of users' behavior

	Mean	s.d.
	(1)	(2)
Register/Log-in	0.1974	(0.3980)
Buy a refrigerator	0.0595	(0.2366)
Number of refrigerator pages viewed	10.1253	(20.8434)
Non-buyers	8.1018	(16.2675)
Buyers	42.0977	(45.0660)
Time spent viewing refrigerator pages (seconds)	734.1172	(1752.428)
Non-buyers	587.102	(1448.952)
Buyers	3057.059	(3561.739)
Number of products added to favorites	0.0373	(0.4097)
Non-buyers	0.0277	(0.3456)
Buyers	0.1886	(0.9537)
Number of products added to cart	0.2270	(0.7109)
Non-buyers	0.1507	(0.5550)
Buyers	1.4327	(1.4410)
Click on energy cost information pop-up	0.0079	(0.1007)
Non-buyers	0.0073	(0.0966)
Buyers	0.0170	(0.1518)

Note: standard deviations in parentheses (Column 2).

Table A4. Treatment effect on purchase decisions: robustness checks

Sample		All users		Buyers (e	xcl. multiple	treatments)	Buyers (ex	xcl. multiple	purchases)
Dependent variable: feature	A+++ or			A+++ or			A+++ or		
of refrigerator bought	more	$\mathbf{A}++$	A+ or less	more	A ++	A+ or less	more	$\mathbf{A}++$	A+ or less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
Treat	-0.002	0.000	0.001	-0.018	-0.008	0.027	-0.023	0.001	0.023
	(0.001)	(0.001)	(0.001)	(0.012)	(0.015)	(0.015)	(0.011)	(0.014)	(0.014)
Mean of dep var	0.010	0.025	0.023	0.167	0.416	0.403	0.176	0.418	0.393
Number of Obs	128167	128167	128167	6318	6318	6318	7341	7341	7341
R-Squared	0.018	0.028	0.030	0.156	0.192	0.194	0.147	0.176	0.181
Panel B									
Treat 1 year	-0.001	0.001	0.001	-0.015	0.009	0.006	-0.024	0.015	0.009
	(0.001)	(0.001)	(0.001)	(0.014)	(0.017)	(0.017)	(0.013)	(0.016)	(0.016)
Treat 15 years	-0.002	-0.001	0.001	-0.021	-0.027	0.049	-0.023	-0.013	0.038
	(0.001)	(0.001)	(0.001)	(0.014)	(0.018)	(0.018)	(0.013)	(0.016)	(0.016)
Mean of dep var	0.010	0.025	0.023	0.167	0.416	0.403	0.176	0.418	0.393
Number of Obs	128167	128167	128167	6318	6318	6318	7341	7341	7341
R-Squared	0.018	0.028	0.030	0.156	0.192	0.195	0.147	0.176	0.182
Price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week f.e	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regressions in all columns. Robust standard errors in parentheses. All regressions control for the average daily prices of refrigerators in classes A+++ or above, A++ and A+ or below; and for week and municipality fixed-effects. Columns 1 to 3 report results for all users, regardless of whether they made a purchase or not; Columns 4 to 6 report results for the sample of buyers, excluding those who were exposed to multiple treatments; Columns 7 to 9 report results for the sample of buyers, excluding those who made multiple purchases.

Table A5. Treatment effect on search outcomes: robustness checks

Dependent variable	Nur	nber of refrige	rator pages vie	we d	Number of seconds spent on refrigerators' pages			
		A+++ or				A+++ or		
	All	more	$\mathbf{A}++$	A+ or less	All	more	\mathbf{A} ++	A+ or less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: sample = all users								
Treat	0.083	0.001	-0.001	0.000	0.738	-4.712	0.113	6.711
	(0.120)	(0.001)	(0.001)	(0.004)	(9.922)	(3.814)	(5.477)	(4.636)
Treat 1 yr	0.158	0.002	-0.001	0.002	5.413	-3.594	1.773	8.731
	(0.138)	(0.001)	(0.001)	(0.004)	(11.241)	(4.330)	(6.278)	(5.349)
Treat 15 yrs	0.006	-0.000	-0.002	-0.002	-4.015	-5.849	-1.574	4.658
	(0.145)	(0.001)	(0.001)	(0.004)	(11.956)	(4.495)	(6.483)	(5.520)
Panel B: sample = buyers (exc	cl. multiple treatn	nents)						
Treat	0.817	0.001	-0.014	0.021	111.686	-25.359	20.262	115.675
	(1.081)	(0.002)	(0.009)	(0.019)	(87.300)	(43.314)	(61.120)	(47.287)
Treat 1 yr	0.870	0.001	-0.013	0.016	85.543	7.306	4.686	68.884
	(1.259)	(0.002)	(0.008)	(0.021)	(101.023)	(51.530)	(69.455)	(55.952)
Treat 15 yrs	0.760	0.001	-0.015	0.026	139.634	-60.282	36.914	165.698
	(1.283)	(0.002)	(0.011)	(0.029)	(105.682)	(48.274)	(74.639)	(56.775)
Panel C: sample = buyers (ex	cl. multiple purch	nases)						
Treat	2.237	-0.001	-0.014	0.033	175.020	-37.872	107.906	95.216
	(1.116)	(0.002)	(0.008)	(0.018)	(84.516)	(44.111)	(60.173)	(44.436)
Treat 1 yr	1.888	-0.001	-0.014	0.026	129.449	-35.486	89.772	65.434
	(1.269)	(0.002)	(0.007)	(0.022)	(96.821)	(50.808)	(68.180)	(53.378)
Treat 15 yrs	2.608	0.000	-0.014	0.041	223.552	-40.414	127.218	126.934
	(1.396)	(0.002)	(0.010)	(0.027)	(105.232)	(52.634)	(74.981)	(51.584)
Price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week f.e	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS regressions in all columns. Robust standard errors in parentheses. All regressions control for the average daily prices of refrigerators in classes A+++ or above, A++ and A+ or below; and for week and municipality fixed-effects. Panel A reports results for all users, regardless of whether they made a purchase or not; Panel B for the sample of buyers, excluding those who were exposed to multiple treatments; Panel C for the sample of buyers, excluding those who made multiple purchases. In each panel, we report the results of two separate regressions: the first is a regression of the outcome on a dummy equal to 1 for being treated; the second on each treatment dummy separately.

Appendix B: Literature on the impact of providing energy cost information on decisions concerning investments in energy efficiency

Study	Product type	Design	N	Treatments	Results	Notes
Anderson and	Refrigerators	In-store field	569	1. Kwh per month;	No difference between	The paper didn't
Claxton (1982)		experiment. 18	refrigerators	2. \$ cost per year;	information treatments.	analyze or make
		stores in 10 cities	(frost-free	3. Sales staff avoid		comparisons of
		in Western	model) were	mentioning energy		the total costs
		Canada,	purchased	consumption;		among different
		randomization at		4. Sales staff communicate		refrigerator
		store level.		lifetime cost.		models.
Allcott and	Lightbulbs	Incentivised	Online: 1,533	Online: 8-years energy and	Online: information	
Taubinsky (2015)		online experiment	respondents;	total cost information;	increases average WTP by	
		and in-store field	Store: 1,087	Store: RAs approached	\$2.3, and market share of	
		experiment, both	customers.	customers in a natural	CFL by 12%;	
		conducted with		setting and provide annual	In-store: no statistically	
		US samples.		energy cost based on their	significant effect of	
				usage.	information.	
Allcott and	Water heaters	Field experiment	23,347	1. Energy cost information;	Information has zero	
Sweeney (2017)		with a store's call	customers;	2. Rebates; 3. Sales agents'	statistical effect.	
		center in the US.	8,275 sales	incentives; and		
				combinations of these		
				treatments.		
Andor, Gerster,	Refrigerators	Stated-choices,	5,000	1. Standard label with	Annual operating cost	
and Sommer		EU sample.	households	annual energy use and	information promotes	
(2016)				efficiency classes; 2. Label	efficient purchases, but only	
				with added annual	when they lead to savings in	
				operating cost information;	the long run.	
				3. Label with added non-		
				energy related information.		
Davis and Metcalf	Air	Online stated-	2,440	1. Standard label; 2. Label	No treatment effect on	Information
(2016)	conditioners	choice experiment	respondents	with state-specific energy	average usage, but	encourages
				cost and usage information.	significant treatment effect	choices
					on allocation: households	associated with
					facing higher costs/usage	lower lifetime
						costs.

					invest more in energy efficiency.	
Deutsch (2010a)	Washing machines	Field experiment with an online price comparison website	95,357 users; 2,065 click- throughs to online retailers.	1. Regular product price information; 2. Additional life-cycle cost information.	Life cycle cost disclosure did not change the retail volume, but decreased the mean specific energy use of chosen washing machines by 0.8%, and their water use by 0.7%.	No data on actual sales, just click-throughs to the webpage of the online retailer.
Deutsch (2010b)	Cooling appliances (refrigerators, fridge- freezers, and freezers)	Field experiment with an online retailer	1,969 click- throughs to online retailers.	Same as Deutsch (2010a).	Life cycle cost disclosure reduces the mean specific energy use of chosen cooling appliances by 2.5%. However, it also decreases the number of clicks from the price comparison website to final retailers by about 23%. However, without controlling for any characteristic of the appliances, information disclosure appears to increase cooling appliances' energy use (page 309, results section).	No data on actual sales, just click-throughs to the webpage of the online retailer.
Heinzle (2012)	TV sets	1. Cost estimation experiment; 2. Stated-choice experiment.	1: 257 participants from a German online panel; 2: 208 respondents.	1.Standard energy use information; 2. Information on annual operating costs.	People over-estimate savings of efficient models. Disclosing lifetime energy operating cost information is effective in guiding consumers towards more efficient purchasing.	
Kallbekken, Sælen, & Hermansen (2013)	Fridge- freezers and tumble driers	Natural field experiment in cooperation with an electrical retailer	5-month period, number of sales not reported.	1. Lifetime energy cost; 2. Training of sales staff; 3. Combination of 1 and 2; 4. Control using data from other untreated stores.	No significant effects of information for fridge-freezers. The combined treatment reduce the average	No randomization, treatment variation at store level. Data on

					energy use of tumble driers sold by 4.9% and 3.4%.	aggregate sale per store only.
McNeill & Wilkie (1979)	Refrigerators	Rating task and build own fridges.	155 female respondents	1. Yearly cost; 2. Yearly cost plus additional information, for example, comparative range.	No consistent effects of information.	
Newell & Siikamäki (2014)	Water heaters	Stated-choice experiments on panel users	1,217 panel members who identify themselves as household head	1. Standard EnergyGuide label; 2. Estimated yearly operating cost; 3. Estimated yearly energy use; 4. Cost range of similar models; 5. CO2 emissions.	Lack of relevant information leads to significant undervaluation of energy efficiency. Simple information on the economic value of saving energy is the most important element.	
Stadelmann & Schubert (2018)	Tumble dryers, freezers and vacuum cleaners	Online retailer	6 months	1. Energy use (kWh); 2. Life-cycle energy cost.	Information did not result in more efficient purchases. It even led to less efficient purchases for vacuum cleaners.	No randomization at individual level. Each treatment implemented for 12 weeks.

Appendix C. Results from Pre-Analysis Plan's specifications

The analysis reported in this section differs from what promised in the Pre-Analysis Plan under two respects, both resulting from the same issue. We were not given access to product catalogue information for other categories of appliances, so we cannot control in the regressions for previous purchases by the customer; nor we can evaluate the impact of the rollout of the energy cost information to other product categories.

Table C1: Treatment effect on the probability that a customer makes a purchase

Dependent variable		Buy a refrigerator						
y	(1)	(2)	(3)	(4)				
Treat	0.005		0.004					
	(0.007)		(0.007)					
Treat 1 year		0.011		0.011				
		(0.008)		(0.009)				
Treat 15 years		-0.000		-0.002				
		(0.007)		(0.008)				
Day f.e.	No	No	Yes	Yes				
Constant	0.313***	0.313***	0.313***	0.313***				
	(0.005)	(0.005)	(0.005)	(0.005)				
Number of Obs	20371	20371	20371	20371				
R-Squared	0.000	0.000	0.018	0.018				

Notes: OLS, s.e. clustered at municipality level. * significant at 10%; *** significant at 5%; *** significant at 1%.

Table C2: Treatment effect on the probability that a customer purchases a product of a certain energy class, unconditional analysis with SUR

Dependent variable	-	igerator of y class
•	(1)	(2)
A+++ or more		
Treat	-0.005	
	(0.003)	
Treat 1 year		-0.004
		(0.004)
Treat 15 years		-0.006
		(0.004)
Constant	0.055***	0.055***
	(0.003)	(0.003)
A++		
Treat	0.000	
	(0.005)	
Treat 1 year		0.007
		(0.006)
Treat 15 years		-0.006
		(0.006)
Constant	0.127***	0.127***
	(0.004)	(0.004)
A+ or less		
Treat	0.010*	
	(0.005)	
Treat 1 year		0.007
		(0.006)
Treat 15 years		0.012**
		(0.006)
Constant	0.127***	0.127***
	(0.004)	(0.004)
Date f.e.	No	No
Number of Obs	20371	20371
R-Squared	0.000	0.000

Notes: SUR regressions. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C3: Treatment effect on purchased products' energy class, conditional analysis

Dependent variable				
	(1)	(2)	(3)	(4)
Treat	0.064**	0.065**		
	(0.030)	(0.030)		
Treat 1 year			0.051	0.054
			(0.039)	(0.037)
Treat 15 years			0.077**	0.076**
			(0.031)	(0.032)
Day f.e.	No	Yes	No	Yes
Constant	2.819***	2.304***	2.819***	2.303***
	(0.076)	(0.198)	(0.076)	(0.198)
Number of Obs	6191	6191	6191	6191

Notes: Ordered probit, s.e. clustered at the municipality level. Excluding minibars (untreated). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C4: Treatment effect on purchased products' characteristics, conditional analysis

Dependent variable	Characteristic of purchased products			
	(1)	(2)	(3)	(4)
Refrigerator's energy c	onsumption (kW	(h)		
Treat	1.987	2.495		
	(2.192)	(2.221)		
Treat 1 year			0.456	0.758
			(2.870)	(2.935)
Treat 15 years			3.566*	4.290*
			(2.122)	(2.189)
Constant	249.978***	249.644***	249.978***	249.643***
	(2.004)	(2.098)	(2.004)	(2.097)
Number of Obs	6271	6271	6271	6271
R-Squared	0.000	0.027	0.000	0.027
Refrigerator's category	,			
Treat	0.028	0.033		
	(0.030)	(0.032)		
Treat 1 year			0.025	0.026
•			(0.042)	(0.043)
Treat 15 years			0.030	0.040
•			(0.031)	(0.033)
Constant	1.105***	1.699***	1.105***	1.699***
	(0.030)	(0.228)	(0.030)	(0.228)
Number of Obs	6208	6208	6208	6208
Refrigerator's price				
Treat	-14.691	-12.150		
	(9.580)	(9.633)		
Treat 1 year	,	, ,	-18.433	-16.768
•			(11.416)	(11.523)
Treat 15 years			-10.822	-7.373
•			(10.320)	(10.418)
Constant	580.421***	578.751***	580.421***	578.750***
	(7.302)	(7.394)	(7.302)	(7.395)
Number of Obs	6187	6187	6187	6187
R-Squared	0.000	0.028	0.000	0.028
Refrigerator's total cos				
Treat	-7.996	-3.886		
	(14.313)	(14.463)		
Treat 1 year	()	(30)	-16.102	-13.285
			(17.693)	(18.101)
Treat 15 years			0.386	5.837
J 3445			(14.651)	(15.044)
Constant	1315.487***	1312.786***	1315.487***	1312.784***
_ 0	(10.983)	(11.263)	(10.984)	(11.263)
Number of Obs	6187	6187	6187	6187
R-Squared	0.000	0.029	0.000	0.029
Day f.e.	No	Yes	No	Yes
Day 1.C.	110	1 68	110	1 68

Note: OLS regressions in Panel A, C and D; Ordered probit regression in Panel B. s.e. clustered at the municipality level. Excluding minibars (untreated). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C5: Treatment effects on navigation

Dependent variable	0	efrigerators product No. Refrigerators' pages pages viewed		Seconds spent on refrigerators' pages		No. Refrigerators added to cart		No. Refrigerators added to favorites		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat	0.253		0.207		39.377**		0.034***		0.027*	
	(0.168)		(0.151)		(19.932)		(0.012)		(0.014)	
Treat 1 year		0.471**		0.329**		52.831**		0.028*		0.043***
		(0.219)		(0.162)		(21.380)		(0.016)		(0.016)
Treat 15 years		0.011		0.068		25.352		0.039**		0.012
		(0.192)		(0.190)		(25.144)		(0.016)		(0.017)
Date f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	11.487***	11.495***	6.717***	6.723***	655.319***	655.540***	0.359***	0.360***	0.136***	0.136***
	(0.151)	(0.151)	(0.124)	(0.124)	(15.437)	(15.312)	(0.009)	(0.009)	(0.010)	(0.010)
Number of Obs	20371	20371	20371	20371	20371	20371	20371	20371	20371	20371
R-Squared	0.010	0.010	0.010	0.010	0.011	0.011	0.010	0.010	0.007	0.007

Notes: OLS, s.e. clustered at municipality level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C6: Treatment effects on navigation, by energy class of products viewed

Energy class of product	A+++ or	more	A++	-	A +	
	(1)	(2)	(3)	(4)	(5)	(6)
Viewed refrigerator's product page						
Treat	-0.009		0.061*		0.079**	
	(0.021)		(0.032)		(0.031)	
Treat 1 year		-0.073		0.086		0.062
		(0.069)		(0.108)		(0.103)
Treat 15 years		-0.006		0.060*		0.080**
		(0.021)		(0.033)		(0.031)
Constant	0.260***	0.280***	0.439***	0.431***	0.526***	0.532***
	(0.018)	(0.028)	(0.028)	(0.043)	(0.027)	(0.041)
Number of Obs	359493	359493	359493	359493	359493	359493
R-Squared	0.010	0.010	0.017	0.017	0.027	0.027
No. Seconds spent on refrigerator's product						
page						
Treat	7.950		-5.501		12.209	
	(6.637)		(9.785)		(9.243)	
Treat 1 year		12.451		19.319		10.156
		(22.061)		(32.526)		(30.722)
Treat 15 years		7.731		-6.706		12.308
		(6.715)		(9.901)		(9.351)
Constant	13.809**	12.390	34.422***	26.598**	14.598*	15.244
	(5.803)	(8.813)	(8.557)	(12.993)	(8.082)	(12.273)
Number of Obs	359493	359493	359493	359493	359493	359493
R-Squared	0.001	0.001	0.002	0.002	0.003	0.003

Notes: OLS individual fixed-effects panel regression, s.e. clustered at municipality level. Additional controls: date f.e. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix D. Estimation of the implied discount rate

We explain here the estimation strategy for the discount rate implied by the observed trade-offs between prices and energy costs, making use of customers' navigation and purchase data. The analysis makes use of the daily variation in purchasing prices and of the information on products views and purchases to estimate implied discount rates. The estimation procedure focuses on the treated consumers and relies on the following assumptions:

- 1. Consumers are fully informed about the energy cost and take this information fully into account.
- 2. Consumers make calculations of energy saving using a constant discounting model with annual discount rate r.
- 3. Consumers take 15 years as the expected life duration. The annual energy cost is paid at the end of each year.
- 4. Based on the above assumptions, a consumer in the 1-year treatment will take $price + f \sum_{t=1}^{15} e^{-rt}$ as the lifetime cost of a fridge, where price is the purchasing price which is incurred immediately, and f the annual energy cost, which is paid each year from year 1 to year 15.
- 5. Similarly, a consumer in the 15-year treatment will take $price + \frac{c}{15} \sum_{t=1}^{15} e^{-rt}$ as the lifetime cost of a fridge, where price is the purchasing price which is incurred immediately, and c the 15-year total energy cost, whose 1/15 is paid each year from year 1 to year 15. In the estimation process, we write $\frac{c}{15}$ as f for consumers assigned into the 15-year treatment.

The analysis makes use of the full navigation data of buyers, where each observation corresponds to one page viewed by a customer. We collapse this dataset at the level of individual, product code and price. This means that we have one observation for each product-price combination viewed by a customer. For instance, if a buyer visited a product page twice during the same day, the product features once among her product views because the same price was applied to the product within the same day. However, if the same product was viewed by the buyer over different days, and experienced a price variation between those days, then the product appears twice in the dataset of that buyer's product views, once for each price. We restrict this dataset to customers assigned to the information treatments who made a purchase, as they are the ones who can be assumed to have full information on the energy costs and to have paid attention to it. The latter assumption is supported by the search outcomes. We take the simple linear model:

$$BuyFridge_{ijt} = \beta_1 + \beta_2 Price_{ti} + \beta_3 f_i + \gamma_t + b_i + t_i + \delta_i + \varepsilon_{ijt}$$

Where $BuyFridge_{ijt}$ is an indicator equal to one if customer i purchased product j on day t. $BuyFridge_{ijt}$ is zero for each product viewed but not purchased. $Price_{tj}$ is the price of product j on day t (time-varying), while f_j is the time-invariant product's energy cost. γ_t are week fixed-effects, indicating the week, within which day t falls; and b_j and t_j are fixed-effects capturing product j's brand and type (one-door, two-doors, fridge-freezer, etc.), two important features of the product.

The coefficients of β_2 and β_3 represents the decision weights of the purchasing price and energy cost for customer *i* while browsing the products. We thus take the ratio of the coefficients $\frac{\beta_3}{\beta_2} = \sum_{t=1}^{15} e^{-rt}$. The discount rate *r* can be computed accordingly. Similarly, we estimate a random effect Logit model where the left-hand side of the equation becomes a latent variable that represents the utility of purchasing the fridge. Table D1 reports the regression results.²⁴

Table D1: Impact of price and energy cost on purchase decisions

Dependent variable	Buys a refrigerator				
-	OLS	Logit			
	(1)	(2)			
Price (\100 Euro)	-0.00396***	-0.1209***			
,	(0.000471)	(0.0105)			
1-year energy cost	-0.000187	-0.00525**			
	(0.000144)	(0.00213)			
Constant	-0.0260				
	(0.0263)				
Observations	43,045	42980			
Number of individuals	5,107	5107			
R-squared	0.011				

Notes: Robust s.e. in parentheses. The regression controls for individual fixed-effects, product brand and type fixed-effects. Product price is expressed in 100 Euro for readability of the results. * significant at 10%; ** significant at 5%; *** significant at 1%.

Based on the above strategy, we have $\frac{\beta_3}{\beta_2} = \sum_{t=1}^{15} e^{-rt} = \frac{-0.000187}{-0.0000396} = 4.72$ and thus r=0.18 from the OLS model, and $\frac{\beta_3}{\beta_2} = \sum_{t=1}^{15} e^{-rt} = \frac{-0.00525}{-0.001209} = 4.34$, and thus r=0.198 from the Logit model.

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²⁴ Note that, for readability of the results, price in the regression is expressed in 100 Euro, while in the calculation of the implied discount rate both price and energy costs are expressed in Euro.