Are energy labels good enough for consumers? Experimental evidence on online appliance purchases

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Are energy labels good enough for consumers? Experimental evidence on online appliance purchases^{*}

Giovanna d’Adda,ⁱⁱ Yu Gaoⁱⁱⁱ and Massimo Tavoni^{iv}

Abstract

We evaluate the impact of adding simple, accurate information to energy labels on consumers’ purchases through a large-scale field experiment with an online retailer of energy-using durables. In addition to the energy efficiency grades and energy usage information included in the standard EU labelling, we provide energy cost information at different aggregation levels. We find that providing lifetime energy costs leads to greater attention paid to low energy-efficiency class products during the search process and more purchasing, but has little impact on energy consumption in kWh or total cost of the products being purchased. Our results suggest that although customers do not understand the labels accurately, they still make nearly optimal decisions based on the coarse signals provided by labels. This is encouraging from a policy perspective because labels simplify the decision process and did not hurt economic-efficiency.

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I. Introduction

Labels, certifications, and grades are widely used to provide coarse information signals such as environmental impact, health and safety, and financial risks. They are very powerful in focusing people's attention on the attribute being graded. They are often required by law to help consumers who have limited ability to retrieve, attend to, and understand complex information (Abaluck and Gruber 2011, 2016; Chetty et al. 2009).

An appliance's energy consumption is often non-transparent, highly complex, and the costs associated with it are distributed over time: these features make it less salient than other appliances' attributes, such as price (Bordalo et al. 2013). Failure to provide consumers with salient and accurate energy cost information may lead to suboptimal choices since such information is essential in computing cost-benefit trade-offs. Nevertheless, in practice, information about energy costs is typically given in Europe and elsewhere, through grading systems or certifications, such as stars, letter-grades, and other coarse rankings, rather than through exact estimates of products' energy costs. Indeed, grading systems commonly mandated by policy makers, help consumers make privately optimal decisions and fill the so-called energy-efficiency gap (Gerarden et al. 2017, 2015; Allcott 2016; Caplin and Dean 2015; Gillingham et al. 2009; Gillingham and Palmer 2014).¹ An implicit belief behind such policies is that detailed information might be ineffective.

In Europe, detailed consumption information is provided in terms of kilowatt-hours (kWh) per year. Translating energy consumption into energy costs requires knowledge of energy prices. As a result, consumers may be reluctant to exert the cognitive effort required to work out appliances' energy costs from information on energy consumption. The grading system provided in addition to the energy consumption information greatly simplifies customers' evaluation of appliances' energy efficiency. However, efficiency classes are imprecisely related to actual energy consumption, due to the relevance of other products' attributes, such as size. In other words, grading systems take into account different product attributes in ways that are not clear to the final user. Therefore, it is possible that detailed cost information could help consumers achieve higher economic efficiency.

We evaluate if grading systems' coarse information is good enough in helping consumers make privately efficient decisions. We conduct a randomized controlled trial (RCT) examining online purchases of large energy-using durables. We focus on refrigerators, one of the most expensive household appliances in terms of price and running costs, the latter being largely independent from usage.² In addition to the grades (A+++, A++, A+ being the most prevalent ones) and kWh consumption information included in the EU energy label, experimental treatments provide yearly or lifetime energy cost information. Observing how consumers' decisions change when accurate information is available in a simpler, more

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

² In Italy, refrigerators are responsible for about 15% of household energy consumption. Source: Enea (Agenzia Nazionale per le Nuove Tecnologie, l'Energia e lo Sviluppo Tecnologico Sostenibile), available at <http://kilowattene.enea.it/KiloWattene-refrigeration-info.html#>.

accessible format will reveal whether consumers rely on coarse signals and whether their private economic efficiency is affected by such reliance.

We partner with a major European online retailer of energy-using durables. Online shopping is a large and rapidly growing market: in 2019, 88% of Europeans reported using the internet, and 63% made purchases online in the previous 12 months.³ This setting gives us access to search as well as purchase data so we can corroborate our findings on decision outcomes with results on the decision-making process.

We find that adding lifetime energy costs information to the coarse signal given by energy labels increases search time and purchases for low energy-class products. However, energy cost information has almost no impact on energy consumption in kWh or total cost of purchased products. Our results show that although the lifetime energy cost treatment is successful in shifting attention and purchasing decisions, suggesting that consumers took the information into account when making their choices, this shift in attention does not affect the private efficiency of decision outcomes. This is a reassuring finding, given coarse signals' prominence as policy tools for promoting private economic efficiency and environmental sustainability.

Our study is one of the first large-scale RCTs to examine the impact of providing information with different levels of complexity, in the presence of coarse signals on the same attribute, on decisions with large stakes. This allows us to make several original contributions to the literature. First, we observe the impact of information on infra-marginal consumers' actual choices in a real online shopping environment. We observe actual purchases, rather than stated preferences elicited through choice experiments (Davis and Metcalf 2016; Newell and Siikamaki 2014); or products placed in the customer's shopping cart (Deutsch 2010b, 2010a). Second, individuals in our sample are not given a shopping budget or other incentives to make purchases, nor are they approached by sales agents or targeted by specific information (Allcott and Taubinsky 2015; Allcott and Wozny 2013; Boogen et al. 2020). They make decisions in a real shopping environment with minimal demand effects. Third, we observe customers' search processes, which allows us to confirm that the information we provide draws customers' attention.

II. Theoretical background and related literature

With empirical evidence dating back to Hausman (1979), there is a long debate on whether consumers are poorly informed or prone to behavioral failures when they trade-off complex product attributes (Allcott 2013; Allcott and Wozny 2013; Chetty et al. 2009; Larrick and Soll 2008). In the domain of energy consumption, failure by individuals to take up privately profitable energy-saving technologies, the so-called energy-efficiency gap, is taken as proof of the presence of such failures and as justification for the provision of information on energy efficiency (Allcott 2016). However, what format such information should take is still a subject of debate.

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³ Eurostat 2019 ICT survey; https://ec.europa.eu/eurostat/statistics-explained/index.php/E-commerce_statistics_for_individuals

On the one hand, researchers justify the provision of information through coarse signals based on the notion of limited attention. Rationally inattentive individuals may choose to act based on incomplete information, rather than incurring costs to become correctly informed (Houde 2018). In the context of purchasing energy-durables, such costs are likely to be high: computing an appliance's lifetime fuel cost requires knowledge of individual discount rates, of the average lifetime of a product and present and future energy prices, together with the ability to calculate present discounted values. Sallee (2014) proposed a theoretical framework to model consumers' rational inattention and uses data on automobiles to show that consumers experience only small welfare losses without detailed information about fuel costs.

On the other hand, providing detailed information affects the adoption of energy-using durables in a wide range of contexts (see Appendix B for a list of studies in this literature). There are two possible mechanisms behind these effects. First, consumers may derive correct information about energy costs from energy labels, but also focus too much attention on the (salient) energy efficiency grades. This may result in consumers preferring products with top efficiency rankings, beyond what is justified by their preferences over energy costs. In this scenario, providing salient and accurate energy cost information may improve decisions' private efficiency by shifting attention from grades to the underlying attribute, cost. Second, consumers may spend too much on energy efficiency in the absence of specific cost information because they overestimate energy costs.⁴ Providing cost information will lead to correctly estimating costs and shift purchases towards products with lower energy consumption in kWh.

Consistent with these theoretical insights, existing evidence shows that labels and grades may have distortionary effects (Darden and McCarthy 2015; Dranove and Jin 2010; Houde 2014; Houde 2018a; Jorion et al. 2005; Newell and Siikamäki 2014; Sammer and Wüstenhagen 2006), and that efficiency gains can result from providing accessible and accurate information to consumers (Davis and Metcalf 2016; Houde 2018b). In particular, Newell and Siikamäki (2014) test various labeling treatments in carefully designed choice experiments: they find that simple information on the economic value of energy savings is the most important element guiding more cost-efficient choices, but that adding a suggestive grade to a model substantially increases the energy efficiency of choices. Despite growing evidence using various methods, the expected effect of adding cost information in a real shopping environment is still ambiguous. Our study aims to fill this gap using an RCT.

Our experimental design, through the provision of energy cost information at two different aggregation levels, also helps disentangle the two above-mentioned mechanisms. If consumers put too much decision weight on the grading system, providing cost information would shift purchases to lower *energy-class* products. We expect this effect to be stronger when providing lifetime energy costs, since aggregation increases their salience (Bordalo et al. 2013). Alternatively, if cost information works by rectifying consumers' overestimation of electricity prices, then we should observe consumers' purchases shift

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⁴ Empirical support for this hypothesis is provided by Bonan et al. (2019), who conducted a survey of a representative sample of 1500 customers of a major Italian energy utility company and found that respondents' average estimate of the price of a kWh was 0.37 euro, almost twice as much as the actual price (around 0.20 euro).

towards products with *lower energy consumption in kWh*, with no significant differences between yearly and lifetime cost information.

II. Experimental design and data

A. Sample

We conducted the field experiment between June 1st and October 16th, 2018, on a major Italian online retailer's website. Our sample comprises customers who viewed or purchased a refrigerator from the desktop version of the website throughout 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 to make a purchase, but not to navigate pages, and through cookie-based identification codes, linked to the computer's IP address and browser, which identify customers who are not logged-in (we describe the procedure we use to identify users from these ID codes in Appendix C). We obtain a sample of 128,206 customers viewed a refrigerator page over the study period.

Treatment assignment was performed by cookie-based software routinely used by the online retailer for A/B 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 clear cookies, she would be exposed to the same treatment on all her subsequent visits. Moreover, once a treatment was associated with a customer ID, it was carried across to other devices or web browsers used by the customer if 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 would attenuate any treatment effect we detect, but otherwise should not compromise 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 the last, so that we have only one refrigerator purchase per user.⁵ We test the robustness of our results to the exclusion of customers who make 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 control condition presented the retailer's default product visualization, with information on energy usage in kWh and the EU-label energy-efficiency class; (b) the 1-year condition

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⁵ 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.

added information on the yearly energy usage cost of each product; and (c) the 15-year condition added information on the lifetime energy usage cost of each product.

The energy cost information was provided through a sentence placed next to an icon reproducing the energy class symbol on 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 product's energy class. The sentence reported the energy usage cost in euro as “Energy costs over 1 year (15 years) will be X euro” in the 1-year (15-year) 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 and the information on a specific product appeared when the customer hovered the mouse over it (see Appendix Figure A1, for a screenshot); and (b) on product pages, where a single product is displayed in detail and the information was placed just below the product image (Figure A2).⁶

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 Italian Authority for Energy, Gas and Water (ARERA) website.⁷ 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 National Agency for New Technologies, Energy and Sustainable Development (Enea) website.⁸ 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 of the information, consistent with the purpose of the study.⁹

The product categories included in the study are free-standing refrigerators (but not minibars) available for delivery during the time of the study. About 2000 products met these criteria in the online retailer's catalogue.

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 on the retailers' website over the study period. The raw data contains information on the municipality of the user's IP address, details on the page visited, whether the internal search engine was used, the search query text, 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,

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⁶ 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 (Appendix Figure A3). Since only 0.7% of users (1.7% of buyers) clicked to open the pop-up window, in what follows we will not analyze this feature.

⁷ The information was taken from the following page: <https://www.arera.it/it/dati/cep35.htm>.

⁸ 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>.

⁹ This is not very different from discounting at the risk-free interest rate in Italy, which was equal to 1.3% at the time and would result in multiplying yearly energy costs by 13.54, instead of 15, to obtain lifetime costs. Using the risk-free rate would further reduce the cost savings from A+++ products.

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. For purchases, we record the product's characteristics, including 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 refrigerator product pages viewed, the number of refrigerators added to the cart, and the favorites, overall and by energy class.¹⁰ For each user, we also record the modal treatment she was exposed to and the number of other (non-refrigerator) orders she placed. 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. Our sample is drawn from municipalities with somewhat higher shares of both high school and university graduates, and income levels than national averages.¹¹

Figure 1. Refrigerators' lifetime energy cost

Note: the graph presents the kernel density of lifetime, i.e., 15-year, energy costs of refrigerators included in the retailer's catalogue, by energy class.

The second set of data comes from the product catalogue, and contains information on refrigerators. For each product, identified by the product code, the data reports a description, brand, category (e.g., one door, fridge-freezer, three doors, etc.), energy class, and yearly consumption in kWh, and the corresponding yearly and lifetime energy costs in euro. The majority of products (50.8%) are in the A+

¹⁰ When collapsing the page-level dataset at the individual level, we correct for multiple observations occurring primarily when customers view their cart, if it contains multiple products: 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 .

¹¹ Comparison made with the dataset of municipalities from Guiso et al. (2016).

energy class, followed by A++ (38%) and A+++ or above (9.5%). On average, refrigerators consume 266 kWh of electricity yearly, equivalent to 53 euro, or 798 euro over 15 years. On average, lifetime energy costs decrease as energy class increases, as expected, ranging from 496 euro for A+++ refrigerators, to 750 euro for A++ and 905 euro for A+. ¹² However, Figure 1, by showing large variations in the distribution of energy costs within energy classes, and significant overlaps of energy costs between classes, confirms that the latter are only coarse indicators of the former. This highlights the potential informational benefits from our experimental treatment.

The third dataset contains daily price information for each refrigerator viewed on the website during the study time. 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. On average, refrigerators cost 660 euro, and prices increase with energy efficiency: A+++ refrigerators cost, on average, almost 300 euro, or 56%, more than products of energy class A+ (Appendix Table A2). Three main factors determine prices. First, the availability of a product in stock: since the online retailer sells its products and products supplied by other sellers, the product price is the lowest available from suppliers with the product 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 results in multiple price updates each day. Third, offers are activated based on 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 over the course of each week: the average difference between the maximum and minimum price for the same product within a week is about 13% of the average price, corresponding to 107 euro for A+++ refrigerators and 71 euro for A+. ¹³

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. 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.

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-year energy cost treatment. About 19.74% of users (25,304) registered or logged into the website at some point. On average, users viewed 10.1 refrigerator 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

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¹² At the time of the study, A+++ minus 10% and A+++ minus 20% refrigerators were available, respectively 10 and 20 % more efficient than the average A+++ refrigerator. The catalogue also includes refrigerators of class A, although they could not be sold by law. Given the low frequency of these instances (less than 0.5% overall), we pool them with A+++ and A+ products and refer to them in the text as A+++ and A+ refrigerators, respectively.

¹³ Appendix Figure A4 displays such price variation, by energy class, over the study period.

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.

Of the 7,631 refrigerator purchases made over the study period, 2,631 are in the control, 2,572 in the 1-year and 2,428 in the 15-year treatments. This corresponds to an overall conversion rate of 5.95%. On average, purchased refrigerators cost 565 euro, about 100 euro, or 14.4%, less than the average refrigerator viewed on the website and included in the retailer's catalogue. Users therefore appear to select among the products available on the retailer's website, the ones with lower prices.¹⁴ On the contrary, energy costs do not, on average, decrease from catalogue to purchases: they decrease, by 78 euro, or 8%, for A+ refrigerators, but increase by 45 euro, or almost 10%, for A+++ ones. These patterns suggest that the salience of product prices, and the lack of salience of energy costs, influences users' selection of which products to buy, among the ones displayed on the retailer's website.

Among purchases, 39.94% were of refrigerators of energy class A+, 42.35% of class A++, and 17.71% of energy class A+++.¹⁵ As energy class rises from A+ to A+++, the price increases, and energy cost decreases. As a result, the average undiscounted total cost, which is a combination of the price and energy cost, is roughly the same for A+++ and A+ refrigerators, 1,260 and 1,220 euro respectively, while it is higher, equal to 1466 euro, for A++ products.¹⁶ Based exclusively on energy costs, A+++ refrigerators would not be worth it for any household with an annual subjective discount rate above 4.4%, which likely includes most households.

B. Treatment effects on purchase decisions

We evaluate the direct impact of adding energy cost information to the energy class and energy usage information available by default from the retailer's website and energy label; 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 linear regression model, with robust standard errors:

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

Where y_{itm} is an outcome for customer i , who visited the website's 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+++, A++, and A+ 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-year energy cost treatments. When we study the decision to purchase a refrigerator, the sample includes all customers who browsed refrigerator pages, regardless of

¹⁴ Indeed, users prefer cheaper products or products on offer: price discounts were applied on 15% of purchases, while 60% of purchases benefited from free delivery. Appendix Table A3 provides summary statistics of users' behavior.

¹⁵ We observe 19 purchases of refrigerators of class A, and 4 purchases in each of the A+++ -10% and A+++ -20% classes.

¹⁶ Appendix Figure A5 displays the distribution of total cost, by energy class, of purchases in the control condition.

whether they registered with the website or bought a refrigerator. When analyzing the characteristics of products bought, our preferred specifications focus on the sub-sample of customers making a purchase.¹⁷

Table 1 reports the impact of being treated (Panel A) and each treatment separately (Panel B). Being treated does not affect the overall likelihood that a customer buys a refrigerator (Column 1). This result holds even when we distinguish between the two treatments. This suggests that our sample of buyers consists of 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 tend to buy refrigerators with higher energy consumption, although only the 15-year treatment effect is significant at the 10% level (Column 2). They also buy cheaper refrigerators (Column 3): this effect is small, a reduction of 18.5 euro, or 3.3%, among treated buyers, and statistically significant at the 5% level overall and the 10% level for the 15-year treatment.¹⁸

We further examine the effect of the energy cost information on the main indicator of private economic efficiency: total cost of purchased refrigerators, which is computed as the sum of sale price and undiscounted lifetime energy cost (Column 4) and find no statistically significant treatment effects. This result is confirmed when we discount energy costs at the risk-free interest rate and at customers' implied discount rate.¹⁹ The distributions of purchased products' energy costs, prices and total cost confirm that the treatment impact on the energy class of purchases translates to minimal shifts in the distribution of energy costs and prices, resulting in almost identical distributions of total costs by treatment (Appendix Figure A7). The seeming contradiction of significant treatment effects on energy class and only marginally significant effects on energy consumption can also be explained by the imperfect correlation between class and consumption, discussed above.²⁰

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¹⁷ This study is registered in the AEA RCT Registry (AEARCTR-0003939). The registered pre-analysis plan (PAP) was submitted before having access to the full set of cleaned data. 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 to benchmark the effect of information. They are absent from the PAP because, at the time of writing it, we did not know that we could exploit daily variations in prices in the analysis. The PAP analysis is reported in Appendix C: its results are robust to alternative specifications, including dropping price controls and Seemingly Unrelated Regressions (SUR), to deal with the correlation between the outcome variables in regressions of treatment effects on purchases' characteristics. The results are also robust to considering the full sample of users; and to excluding buyers exposed to multiple treatments, or who made multiple purchases (Appendix Table A4).

¹⁸ Sale price information is not available for 90 refrigerators, which explains the drop in the number of observations in Columns 3-4 of Table 1.

¹⁹ Exploiting the daily variation in prices and the detailed information available on customers' navigation history, we estimate an implied discount rate equal to 18% or 19.8%: this is very close to the elicitation in Newell and Siikamaki (2015) of 19% on average. The estimation framework is analogous to the attention weight models in Allcott and Wozny (2013), Newell and Siikamaki (2015), Chetty et al. (2009) and DellaVigna (2009). Appendix D provides further details of the estimation theoretical framework, assumptions and results. Table D2 also reports the treatment effects on total cost when discounting energy costs at the risk free and implied rates.

²⁰ Appendix Figure A6 displays the marginal treatment effects on energy class, consumption, price and total cost of purchases from the regressions. Appendix Table A5 instead shows that treated customers do not buy smaller refrigerators, measured by capacity in liters.

In terms of the energy class of purchases, treated customers buy fewer of the most efficient products and more of the least efficient ones (Columns 5-7): the treatment effect on the likelihood of purchasing an A+++ refrigerator is significant at the 5% level. This effect is driven by the 15-year treatment, which increases the share of least efficient purchases by 9.1%, or 3.6 percentage points ($p < 0.05$).²¹ The effects of the two treatments are generally not significantly different from each other, except that the 15-year treatment has a significantly larger impact than the 1-year on the likelihood that customers buy an A+ refrigerator and on the energy consumption of purchases (both $p < 0.1$).

Prices correlate 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) with A+ products, while they do not seem to switch between A+++ and A++ products as their relative prices change. This matches the pattern of 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 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-year 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% increase in price.

Table 1. Treatment effects on purchases

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

Note: OLS regressions. Robust standard errors in parentheses. All regressions control for week and municipality fixed-effects. Panel A examines the impact of being treated, while Panel B distinguishes between the two treatments.

C. Treatment effect on search patterns

The results on purchases indicate that providing information on energy costs on top of the energy labels 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. This analysis's outcome variables are the number of refrigerator product pages viewed and the time spent browsing them.

While we observe no treatment effects on search outcomes for the full sample of users, in terms of total number of pages viewed or the time spent on them (Appendix Table A6), 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 refrigerator pages and spend 188 more seconds searching, an increase of 5.2 ($p < 0.1$) and 6.2% ($p < 0.05$) over the mean of the dependent variable, respectively. In both cases, the result is driven by the 15-year treatment, with treatment effects significant at the 1% 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 spend 102 and 98 seconds more on products in classes A++ and A+, respectively. This corresponds to a 7.7 ($p < 0.1$) and 9.4% ($p < 0.05$) increase in time spent viewing refrigerators of energy class A++ and A+, respectively. As in the analysis of purchase decisions, these results are driven by the 15-year treatment, which leads to an 11.9 ($p < 0.05$) and 13.4% ($p < 0.01$) increase in products viewed and search time, respectively.²²

Product prices do not appear to determine the choice of which products to view. Still, they do affect the time spent viewing products in different energy classes, a pattern consistent with that 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.

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²² Appendix Figure A8 shows marginal treatment effects on search time, and Table A6 shows that the results are robust to alternative definitions of the sample.

Table 2. Treatment effects on search: buyers

Dependent variable	Number of refrigerator pages viewed				Number of seconds spent on refrigerators' pages			
	All	A+++	A++	A+	All	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A</i>								
Treat	2.217 (1.173)	0.000 (0.002)	-0.010 (0.008)	0.036 (0.018)	188.334 (88.235)	-24.028 (44.618)	102.237 (60.622)	97.908 (45.627)
Avg. Daily price A+++	1.302 (1.449)	0.000 (0.001)	-0.001 (0.005)	-0.045 (0.028)	-64.320 (103.570)	-76.072 (52.523)	-8.278 (69.586)	44.092 (55.723)
Avg. Daily price A++	-1.444 (1.943)	0.004 (0.003)	0.008 (0.007)	0.061 (0.048)	-117.206 (142.291)	36.068 (72.969)	-143.195 (93.698)	-24.167 (77.596)
Avg. Daily price A+	-0.248 (2.259)	0.000 (0.003)	-0.000 (0.010)	-0.072 (0.047)	36.778 (177.988)	156.217 (84.909)	-12.815 (120.565)	-96.650 (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
<i>Panel B</i>								
Treat 1-year	1.370 (1.319)	-0.000 (0.002)	-0.011 (0.007)	0.036 (0.023)	96.047 (99.911)	-25.161 (51.013)	50.410 (68.278)	58.043 (53.841)
Treat 15-year	3.116 (1.469)	0.001 (0.002)	-0.009 (0.010)	0.036 (0.027)	286.191 (110.587)	-22.827 (53.312)	157.193 (75.810)	140.179 (54.526)
Avg. Daily price A+++	1.288 (1.449)	0.000 (0.001)	-0.001 (0.005)	-0.045 (0.028)	-65.826 (103.541)	-76.091 (52.462)	-9.123 (69.622)	43.441 (55.656)
Avg. Daily price A++	-1.443 (1.943)	0.004 (0.003)	0.008 (0.007)	0.061 (0.048)	-117.102 (142.269)	36.069 (72.972)	-143.137 (93.725)	-24.122 (77.585)
Avg. Daily price A+	-0.215 (2.257)	0.000 (0.003)	-0.000 (0.010)	-0.072 (0.047)	40.470 (177.823)	156.262 (84.841)	-10.741 (120.359)	-95.055 (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: 1-yr = 15-yr	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. Panel A examines the impact of being treated, while Panel B distinguishes between the two treatments.

IV. Conclusions

Our analysis shows that providing information on energy-using appliances' energy costs, on top of the energy class and usage information included in the standard EU energy label, affects the energy-efficiency class, but not the energy consumption in kWh and total cost of purchases. This result is consistent with consumers' overweighting energy class in their purchase decisions, possibly due to its salience within the standard energy label. The information on lifetime energy cost reduces the prominence of energy class and leads to fewer purchases among products in the highest efficiency class. The finding that treatments increase search time on low energy-efficacy class products also supports this interpretation. We find no evidence of imperfect information on electricity price among users since our treatments did not affect the total cost of products being purchased.

Overall, our results indicate that consumers rely on coarse signals when acquiring information. We find that the cost of this tendency in terms of the private economic efficiency of decisions is likely to be low, given the limited impact of providing simple but accurate cost information on the total cost of purchases.

This result is encouraging from a policy perspective and supports the use of grading systems to help consumers understand complex and policy-relevant products' attributes.

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Appendix A: Table and Figures

Figure A1. Listing page

a. Control

The screenshot shows a web page for refrigerators. The left sidebar has filters for 'Frigoriferi', 'Frigoriferi Combinati', and 'Frigoriferi Side by Side'. The main content area displays a grid of refrigerator models. The first row shows four models: Samsung RB417859SR, Bosch KGN39VL45, Samsung RB33N300NSA, and Samsung RB33J80355R. The second row shows four models: Samsung RB37J5315EF, Samsung RB31FEJNCSA, Samsung RB29FERNCSA, and Samsung RB29FERNDSA. Each model is shown with its image, name, price, and rating. The prices range from €458.99 to €899.99. The ratings range from 4.3 to 4.7 stars. The page also includes a 'Filtrare per' section with options for 'Sconti alla Rovescia', 'Solo promozioni', and 'Disponibili'. The 'Classe Energetica' section shows options for A+, A++, and A+++.

b. 1-year condition

This screenshot is identical to the one above, showing the same refrigerator listing page. It displays a grid of refrigerator models with their images, names, prices, and ratings. The left sidebar contains filters for product type, price, and energy class. The main content area displays various Samsung and Bosch refrigerator models. The prices range from €458.99 to €899.99. The ratings range from 4.3 to 4.7 stars. The page also includes a 'Filtrare per' section with options for 'Sconti alla Rovescia', 'Solo promozioni', and 'Disponibili'. The 'Classe Energetica' section shows options for A+, A++, and A+++.

c. 15-year Condition

← → × [https://www.elettrodomestici.it/elettrodomestici-cucina/grandi-elettrodomestici...](#) 🔍 ☆

PIÙ SCELTE

FILTRA I PRODOTTI

Scegli per

- ☐ Sconti alla Rovescia (2 articoli)
- ☐ Solo promozioni (152)
- ☒ Disponibili (1502)
- ☐ Consegna in 24/48 h (176)

Marche

- ☐ BOSCH (176 articoli)
- ☐ SMEG (71)
- ☐ SAMSUNG (47)
- ☐ BEKO (43)
- ☐ LIEBHERR (41)
- ☐ WHIRLPOOL (39)
- ☐ ELECTROLUX (33)
- ☐ HOTPOINT (28)
- ☐ LG (26)
- ☐ BOMPANI (23)
- ▼ PIÙ SCELTE

Total No Frost

- ☐ SI (309 articoli)

Dual No Frost

- ☐ SI (3 articoli)

Classe Energetica

- ☐ A+ (175 articoli)
- ☐ A++ (271)
- ☐ A+++ (102)
- ☐ A+++ -20% (1)
- ☐ A+++ -20% (1)
- ▼ PIÙ SCELTE

Raffreddamento Vano Frigo

1 2 3 4 5 6 7 8 9 10

BOSCH - KGN39VL45 Frigorifero Combinato Capacità Lorda / Netta
€ 599,99 Risparmio 35%
CONSEGNA GRATIS
★★★★★ 4.5 (55)
A+++ - Spendi € 545,45 di energia in 15 anni
Venduto e spedito da ePRICE. Altre offerte.

SAMSUNG - Frigorifero Combinato RB29FERND5A Linea Smart No Frost
€ 505,99
CONSEGNA GRATIS
★★★★★ 4.6 (46)

INDESIT - Frigorifero Combinato NCA55 NIX Classe A+ Capacità
€ 310,99
CONSEGNA GRATIS
★★★★★ 4.2 (24)

SAMSUNG - Frigorifero Combinato RB37J5209SA No Frost Premium
€ 794,99
CONSEGNA GRATIS
★★★★★ 4.6 (42)

SAMSUNG - Frigorifero Combinato RB33N300NSA No Frost Classe A+++
€ 558,99
CONSEGNA GRATIS
★★★★★ 4.7 (6)

BOSCH - Frigorifero Combinato KGN36NW30 No Frost Classe A++
€ 460,99
CONSEGNA GRATIS
★★★★★ 4.3 (19)

BOSCH - Frigorifero Combinato KGN36NL30 Capacità Lorda / Netta
€ 477,99
CONSEGNA GRATIS
★★★★★ 4.6 (44)

HOTPOINT - Frigorifero Combinato XHBT3ZXQZH Total No Frost Classe
€ 639,99
CONSEGNA GRATIS
★★★★★ 4.7 (18)

a. Control

b. 1-year condition

20

c. 15-year condition

Classe Energetica	A+++ Spendi € 545,45 di energia in 15 anni
Raffreddamento Vano Congelatore	No Frost
Cardini Porta	Reversibili
Altezza	203 cm
Profondità	66 cm
Total No Frost	Si

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 maggior tutela, consumi annui di 2.700 kWh e potenza impegnata di 3 kW), pari a 0,1998€ (fonte: dati ARERA, secondo trimestre 2018²).
La vita media di un frigorifero è stimata pari a 15 anni (fonte: ENEA³).

Con questo prodotto **classe A+++**
in **1 anno** spendi

€ 36,36

CHIUDI E PROSEGUI CON GLI ACQUISTI

In collaborazione con il progetto COBHAM del Politecnico di Milano ⁴

² Sito ARERA
³ Sito Enea
⁴ ERC grant agreement n° 336155 - progetto COBHAM: "The role of consumer behaviour and heterogeneity in the integrated assessment of energy and climate policies".

b. 15-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 maggior tutela, consumi annui di 2.700 kWh e potenza impegnata di 3 kW), pari a 0,1998€ (fonte: dati ARERA, secondo trimestre 2018²).
La vita media di un frigorifero è stimata pari a 15 anni (fonte: ENEA³).

Con questo prodotto **classe A+++**
in **15 anni** spendi

€ 545,45

CHIUDI E PROSEGUI CON GLI ACQUISTI

In collaborazione con il progetto COBHAM del Politecnico di Milano ⁴

² Sito ARERA
³ Sito Enea
⁴ ERC grant agreement n° 336155 - progetto COBHAM: "The role of consumer behaviour and heterogeneity in the integrated assessment of energy and climate policies".

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. Distribution of total cost of purchases

Note: kernel density of total cost of purchases, where total cost is defined as the sum of the price and of the undiscounted lifetime energy cost, by energy class.

Figure A6. Marginal treatment effects: characteristics of purchases

Notes: marginal treatment effects, computed from the coefficients of equation (1). Price and total cost are expressed in euro.

Figure A7. Distribution of lifetime energy costs, price and total cost of purchases, by treatment

Note: kernel density of undiscounted lifetime energy cost, price and total cost of purchases, where total cost is defined as the sum of the price and of the undiscounted lifetime energy cost, by treatment.

Figure A8. Marginal treatment effects: search behavior

Notes: marginal treatment effects, computed from the coefficients of equation (1). Price and total cost are expressed in euro.

Table A1. Price of refrigerators

	Mean (sd)
Avg. daily price	660.04 (29.83)
Avg. Daily price A+++	815.66 (48.61)
Avg. Daily price A++	770.34 (37.07)
Avg. Daily price A+	522.57 (40.85)
Weekly variation in price A+++	107.24 (65.16)
Weekly variation in price A++	87.40 (29.29)
Weekly variation in price A+	71.22 (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 (1)	p-value (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 $\beta(1\text{-year treatment}) = \beta(15\text{-year treatment}) = 0$, 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 (1)	s.d. (2)
Register/Log-in	0.1974	(0.3980)
Buy a refrigerator	0.0595	(0.2366)
Number of refrigerator pages viewed	10.1253	(20.8434)
<i>Non-buyers</i>	<i>8.1018</i>	<i>(16.2675)</i>
<i>Buyers</i>	<i>42.0977</i>	<i>(45.0660)</i>
Time spent viewing refrigerator pages (seconds)	734.1172	(1752.428)
<i>Non-buyers</i>	<i>587.102</i>	<i>(1448.952)</i>
<i>Buyers</i>	<i>3057.059</i>	<i>(3561.739)</i>
Number of products added to favorites	0.0373	(0.4097)
<i>Non-buyers</i>	<i>0.0277</i>	<i>(0.3456)</i>
<i>Buyers</i>	<i>0.1886</i>	<i>(0.9537)</i>
Number of products added to cart	0.2270	(0.7109)
<i>Non-buyers</i>	<i>0.1507</i>	<i>(0.5550)</i>
<i>Buyers</i>	<i>1.4327</i>	<i>(1.4410)</i>
Click on energy cost information pop-up	0.0079	(0.1007)
<i>Non-buyers</i>	<i>0.0073</i>	<i>(0.0966)</i>
<i>Buyers</i>	<i>0.0170</i>	<i>(0.1518)</i>

Note: standard deviations in parentheses (Column 2).

Table A4. Treatment effect on purchase decisions: robustness checks

Sample Dependent variable: feature of refrigerator bought	All users			Buyers (excl. multiple treatments)			Buyers (excl. multiple purchases)		
	A+++	A++	A+	A+++	A++	A+	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel A</i>									
Treat	-0.002 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.018 (0.012)	-0.008 (0.015)	0.027 (0.015)	-0.023 (0.011)	0.001 (0.014)	0.023 (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
<i>Panel B</i>									
Treat 1-year	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.015 (0.014)	0.009 (0.017)	0.006 (0.017)	-0.024 (0.013)	0.015 (0.016)	0.009 (0.016)
Treat 15-year	-0.002 (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.021 (0.014)	-0.027 (0.018)	0.049 (0.018)	-0.023 (0.013)	-0.013 (0.016)	0.038 (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+++ , A++ and A+; 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 effects on purchased refrigerators' capacity

Dependent variable	Refrigerator's capacity (liters)	
	(1)	(2)
Treat	-2.366 (3.695)	
Treat 1-year		-4.790 (4.219)
Treat 15-year		0.200 (4.356)
Mean of dep var	359.462	359.462
Number of Obs	6599	6599
R-Squared	0.205	0.205

Note: OLS regressions in all columns. Robust standard errors in parentheses. All regressions control for the average daily prices of refrigerators in classes A+++, A++ and A+; and for week and municipality fixed-effects. Capacity is defined as gross capacity in liters, or as net capacity whenever gross capacity information was missing.

Table A6. Treatment effect on search outcomes: robustness checks

Dependent variable	Number of refrigerator pages viewed				Number of seconds spent on refrigerators' pages			
	All	A+++	A++	A+	All	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: sample = all users</i>								
Treat	0.083 (0.120)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.004)	0.738 (9.922)	-4.712 (3.814)	0.113 (5.477)	6.711 (4.636)
Treat 1-year	0.158 (0.138)	0.002 (0.001)	-0.001 (0.001)	0.002 (0.004)	5.413 (11.241)	-3.594 (4.330)	1.773 (6.278)	8.731 (5.349)
Treat 15-year	0.006 (0.145)	-0.000 (0.001)	-0.002 (0.001)	-0.002 (0.004)	-4.015 (11.956)	-5.849 (4.495)	-1.574 (6.483)	4.658 (5.520)
<i>Panel B: sample = buyers (excl. multiple treatments)</i>								
Treat	0.817 (1.081)	0.001 (0.002)	-0.014 (0.009)	0.021 (0.019)	111.686 (87.300)	-25.359 (43.314)	20.262 (61.120)	115.675 (47.287)
Treat 1-year	0.870 (1.259)	0.001 (0.002)	-0.013 (0.008)	0.016 (0.021)	85.543 (101.023)	7.306 (51.530)	4.686 (69.455)	68.884 (55.952)
Treat 15-year	0.760 (1.283)	0.001 (0.002)	-0.015 (0.011)	0.026 (0.029)	139.634 (105.682)	-60.282 (48.274)	36.914 (74.639)	165.698 (56.775)
<i>Panel C: sample = buyers (excl. multiple purchases)</i>								
Treat	2.237 (1.116)	-0.001 (0.002)	-0.014 (0.008)	0.033 (0.018)	175.020 (84.516)	-37.872 (44.111)	107.906 (60.173)	95.216 (44.436)
Treat 1-year	1.888 (1.269)	-0.001 (0.002)	-0.014 (0.007)	0.026 (0.022)	129.449 (96.821)	-35.486 (50.808)	89.772 (68.180)	65.434 (53.378)
Treat 15-year	2.608 (1.396)	0.000 (0.002)	-0.014 (0.010)	0.041 (0.027)	223.552 (105.232)	-40.414 (52.634)	127.218 (74.981)	126.934 (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+++, A++ and A+; 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.

Figures

Figure 1

Refrigerators' lifetime energy cost. Note: the graph presents the kernel density of lifetime, i.e., 15-year, energy costs of refrigerators included in the retailer's catalogue, by energy class.

Supplementary Files

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