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A randomized trial of energy cost information provision alongside energy-efficiency classes for refrigerator purchases

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Energy-efficiency classes provide coarse but easy-to-process information designed to help complex decisions. However, they are multi-attribute indices, imprecisely related to the running costs of graded products. Here we evaluate the impact of adding simple but accurate yearly or lifetime energy cost information to the European Union energy label. We conduct a field experiment with an online retailer of energy-using durables, measuring customers' ($n = 126{,}614$) search and purchases of refrigerators. Providing precise energy costs leads to purchasing products with lower prices and in lower energy-efficiency classes, but with similar overall energy and total costs. Furthermore, information provision lengthens product search among buyers, with more attention paid to low energy class products. These results highlight that the use of energy classes involves a trade-off between short-term economic savings and higher search cost. By drawing attention away from energy costs, energy-efficiency classes might not be adequate in the context of a fair and transparent climate transition.

The use of energy-efficiency labels is mandated by law in Europe, the United States and many other countries to inform consumers and help them trade-off complex product attributes[1–7]. The energy usage of durable goods is a non-transparent, complex and time-varying attribute; computing running costs requires knowledge of individual discount rates, products' average lifetimes and present and future energy prices. Their distribution over time also makes running costs less salient than other product attributes, such as price[8–12].

Labels around the world differ primarily along two dimensions: whether they compare appliances across energy-efficiency categories, such as stars, letter grades and other coarse rankings, or along a continuous linear scale; and whether they provide information on appliances' consumption in monetary or physical (for example, kilowatt-hours, kWh) units. Energy-efficiency classes and consumption information in physical units characterize the labels adopted in many countries, such as the European Union (EU) countries, China, India, Brazil, Australia, Saudi Arabia and South Korea. The United States and Canadian labels are prominent examples of certifications displaying energy consumption on a continuous scale and through monetary units.

The design of energy labels involves trade-offs between simplicity and accuracy. The provision of information through coarse signals, such as energy-efficiency classes, is justified on the basis of limited attention and cognitive capacity[13,14]. However, grading systems consider different product attributes, such as size, in ways that are not clear to the final user, and are imprecisely related to actual running costs. On the other hand, detailed monetary costs provide more accurate energy-efficiency information in units with a clear meaning for consumers. However, they may be misleading in the presence of large variations in energy prices[15]. Similarly, life-cycle energy-efficiency information may be more relevant for the consumer, but providing it requires assumptions on appliances' lifetime and discount rates that increase the complexity of the information and reduce its transparency.

The evidence on how the design of energy labels affects investments in energy efficiency is mixed and comes predominantly from hypothetical experiments and surveys[13,16–19]. Recent studies suggest that more information may reduce social welfare[13,20]. Despite growing evidence, the effect of adding information on the running cost of large appliances at varying levels of temporal aggregation to energy-efficiency classes in a natural shopping environment is still ambiguous[21–23].

In this article, we evaluate the impact of adding accurate cost information to coarse signals provided through energy-efficiency classes on consumers' choices focusing on the EU energy label. We conduct a randomized controlled trial (RCT) in Italy examining online purchases of refrigerators. Refrigerators are among the most expensive household appliances in terms of price and running costs, which account for 15% of household energy consumption and are largely independent of usage[24]. The online setting allows us to observe behaviour under minimal demand effects and gives us access to consumers' search and purchasing data to examine the decision-making process and its outcomes. It is also an increasingly relevant setting: while only about 16% of appliance sales occurred online during 2018 in Italy, 74% of buyers of large appliances start the search process online[25,26]. Furthermore, restrictions due to the COVID-19 pandemic have caused a 64% increase in online sales in Europe, which has not vanished since physical shops re-opened[27,28].

We find that adding energy costs information to energy labels does not affect the overall likelihood of purchasing a refrigerator, but shifts the distribution of purchases away from top-ranked A+++ products toward lower-graded ones with lower prices. Such a shift does not come at the expense of higher energy costs, since the distributions of energy costs of the different classes overlap. Processing the energy cost information requires attention and

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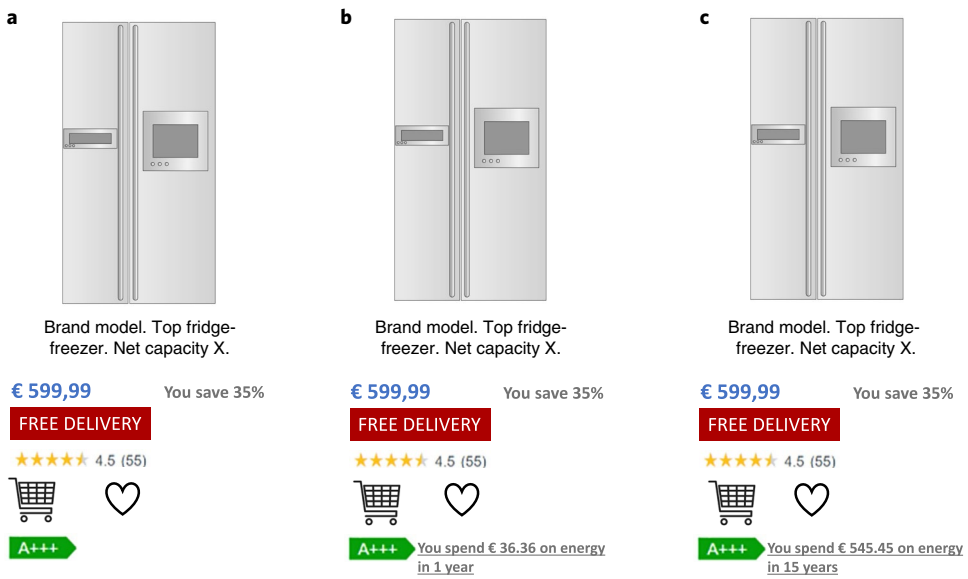

Fig. 1 | Product listing page display for control and treatment groups. The figure presents a product, as displayed on the retailer's listing page. **a**, Users in the control treatment view the product's name and code, its price, information on any promotion active on the product and its energy class through a symbol that reminds them of the visualization adopted in the EU energy label. **b**,**c**, Users in the 1-year (**b**) and 15-year (**c**) treatments view, in addition, a sentence reporting the yearly (**b**) or lifetime (**c**) energy cost of the product, respectively.

takes time: treated buyers view more products and spend more time searching, devoting the additional search time to lower-ranked A+ products. As the search progresses, treated users view products of lower-efficiency class, price and total cost (that is, price plus lifetime energy cost), relative to users in the control group. Our findings are consistent with labels drawing consumers' attention to the (salient) energy-efficiency grades, rather than the underlying energy cost, and with efficiency classes being an imperfect proxy of energy consumption. They also highlight the trade-off between economic savings and higher search costs in providing running cost information.

Experimental design and data

We conducted an RCT on a major Italian online retailer's website. Our sample comprises customers who viewed a refrigerator from the desktop version of the website between 1 June and 16 October 2018 ($n = 126{,}614$). Each customer visiting the retailer's website for the first time during this period was randomly assigned to one of three treatments: (1) the control treatment consisted of the retailer's standard website, with information on refrigerators' energy usage in kWh and the EU label energy-efficiency class ($n = 43{,}101$); (2) the 1-year treatment added information on products' yearly energy usage cost ($n = 42{,}157$) and (3) the 15-year treatment added information on products' lifetime energy usage cost ($n = 41{,}356$). 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). We provided the energy expenditure information in two places on the website: (1) on product listing pages, where products are displayed in a list, and the information on a specific product appears when the customer hovers the mouse over it (Fig. 1, the Italian version is shown in Supplementary Fig. 1); and (2) on product pages, where a single product is displayed in detail and the information is located just below the product image (Supplementary Fig. 2).

The EU energy label provides detailed consumption in kWh per year and classifies products into efficiency classes through letter grades. At the time of the study, the prevalent classes were A+++, A++ and A+, and higher classes were associated with higher efficiency ranking. The energy-efficiency class of a refrigerator depends on its energy consumption relative to a benchmark. Such benchmark is a function of several features of the appliance, including its volume, the storage temperature of its different compartments and whether it is frost-free, built-in and has an ice-maker. The calculation behind energy classes indicates that refrigerators with similar energy consumption may be assigned to different classes. Supplementary Note 1 details the energy class calculation in the EU label and in similar labels in other countries.

The analysis combines four sources of data. The first source is the navigation data extracted daily from the online retailer. The dataset contains one observation per page visited, for all users who visited the retailers' website over the study period. It provides information on the municipality of the user's internet protocol (IP) address, details on the page visited, the time of the page visit and the number of seconds spent viewing the page. Second, we collected data from the retailer's product catalogue on refrigerators' characteristics, including energy class, yearly energy consumption in kWh, yearly and lifetime energy cost in euros (€), category (for example, one door, fridge-freezer, three doors and so on) and capacity. The third data source is the daily price information for each refrigerator viewed on the website during the study time. Finally, we have municipal-level data on population, income, education and other socioeconomic characteristics[29], which we match to the municipality of the user's IP address. This means that we have no individual-level information on users, and assessment of randomization balance relies on municipal-level data (Supplementary Table 1).

On average, viewed refrigerators cost €668 and the price increases with energy efficiency: an average A+++ refrigerator costs almost €300, or 52%, more than an average A+ refrigerator (Supplementary Table 2). Prices vary greatly—by as much as 13% of the average price—over a week, due to variations in products availability in stock, competitors' prices and promotions (Supplementary Fig. 3). Energy cost of viewed products, which is on average €53 per year or €797 over 15 years, decreases with energy efficiency, from €879 over 15 years for A+ refrigerators to €822 for A++ and €537 for A+++. As a result, the undiscounted total cost of viewed products, which is the sum of the price and energy cost over the product lifetime, is on average lowest for A+++ refrigerators (€1,351), higher for A+ ones (€1,413) and highest (€1,593) for A++ products.

Table 1 | Treatment effects on purchases

Sample	All	Buyers					
Dependent variable	Buys a refrigerator	Feature of refrigerator bought					
		Lifetime energy cost (€)	Price (€)	Total cost (€)	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	−0.001	4.722	−19.985**	−13.719	−0.021**	−0.001	0.023*
	(0.001)	(6.526)	(9.646)	(13.663)	(0.011)	(0.014)	(0.013)
Average daily price A+++	−0.006***	2.398	−11.684	−10.676	−0.052***	0.018	0.035**
	(0.002)	(8.470)	(13.256)	(18.835)	(0.012)	(0.018)	(0.018)
Average daily price A++	−0.008***	13.491	32.961**	48.880**	0.013	−0.071***	0.050**
	(0.002)	(10.170)	(14.671)	(20.880)	(0.016)	(0.021)	(0.021)
Average daily price A+	0.004	26.746**	64.768***	87.331***	0.049**	0.062**	−0.104***
	(0.003)	(12.991)	(18.842)	(27.093)	(0.021)	(0.027)	(0.027)
Observations	126,614	7,635	7,545	7,545	7,635	7,635	7,635
R-squared	0.029	0.185	0.221	0.213	0.146	0.175	0.179
Mean control	0.061	755.3	577	1,332	0.188	0.415	0.384

Note that ordinary least squares (OLS) regressions are used. Robust standard errors are in parentheses. All regressions control for week and municipality-fixed effects. 'Treat' is a dummy equal to one for users whose modal treatment is one of the two energy cost information treatments. Average daily prices indicate the average price of refrigerators in the different energy classes on the day of the purchase for buyers or the first day of navigation for non-buyers: the coefficients on these variables capture the impact of a €100 increase in prices. Column 1 considers the full sample of users, while columns 2–7 consider the sample of buyers. The fewer observations in columns 3 and 4 are due to missing product-price data. The table reports the mean of the dependent variable in the control group. No adjustments were made for multiple comparisons. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

These average figures mask great within-class variability, as discussed in what follows.

We observe 7,635 refrigerator purchases over the study period. Of these, 34.5% ($n=2{,}634$) are in the control, 33.7% ($n=2{,}571$) in the 1-year and 31.8% ($n=2{,}430$) in the 15-year treatments. This corresponds to an overall conversion rate of 6%. A++ refrigerators account for the highest share of purchases at 42.3% ($n=3{,}189$), followed by A+ at 40% ($n=3{,}010$) and A+++ at 17.7% ($n=1{,}335$). On average, users view 10.1 refrigerators' product and cart pages, ranging between 8 for those who do not make a purchase and 41.8 for those who do. Buyers and non-buyers view, on average, seven and three distinct refrigerators, respectively. This corresponds to an average of 751 seconds spent browsing, 3,203 (about 53 minutes) among buyers and 594 (10 minutes) among non-buyers. The first product viewed is an A+ for about 46% of users, an A++ for 39% and an A+++ for 14%. About 88% of users end up buying a refrigerator in the same energy class as the first product that they view.

Treatment effects on purchase decisions

We first evaluate the direct impact of adding energy cost information to the energy class and energy usage information available by default on the likelihood of making a purchase, and the characteristics of refrigerators bought. When we study the decision to purchase a refrigerator, the sample includes all customers who browsed refrigerator pages. We restrict attention to buyers when analysing the characteristics of purchases. In the main text, we present the results with the two treatments pooled and comment on their differential impact, which we display in Supplementary Table 4.

Table 1 shows regression results. We comment both on the point estimates and on the 95% confidence intervals around them, to better interpret these results. Being treated does not affect the overall likelihood that a user buys a refrigerator (column 1). Since users have the outside options of not purchasing a refrigerator or purchasing it elsewhere, and our data do not allow us to monitor what users do when they leave the retailer's website, this result is important because it indicates that the treatment does not significantly affect such outside options. Treated customers buy cheaper refrigerators (column 3, $\beta=-19.985$, $P<0.05$). With 95% likelihood, the prices of purchases decrease between €1.1 and €38.9. This is consistent with the fact that they are 11% less likely to buy more expensive A+++ products (column 5, $\beta=-0.021$, $P<0.05$), and correspondingly more likely to buy cheaper A+ ones (column 7, $\beta=0.023$, $P<0.1$). Despite this shift in purchases from higher to lower-efficiency classes, the average energy cost of refrigerators bought is not significantly higher among treated users (column 2, $\beta=4.722$): the change in energy cost caused by the treatment ranges between €−8.1 and €17.5 with 95% likelihood. The treatment does not significantly reduce the total cost of purchases (column 4, $\beta=-13.719$), with the 95% confidence interval ranging between €−40.5 and €13.1. This result holds even when discounting energy costs at customers' implied discount rates or the risk-free interest rate (Supplementary Information and Supplementary Table 3). These findings indicate that our experiment can only imprecisely detect the treatment effects, and that insignificant coefficients hide effects that are at most equal to a 6% decrease in the price, 2% increase in the lifetime energy cost and 3% increase in the total cost of purchases.

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 one on the likelihood that customers buy an A+ refrigerator and on the lifetime energy cost of purchases (Supplementary Table 4, Wald tests of difference between coefficients, both *P*s <0.1). Results are qualitatively robust to different specifications and definitions of the sample and the treatment indicator, to deal with users who make more than one purchase or are exposed to multiple treatments (Supplementary Tables 5–11). They are not due to treated users buying smaller refrigerators (Supplementary Table 12).

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) for 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. The impact of information on energy costs

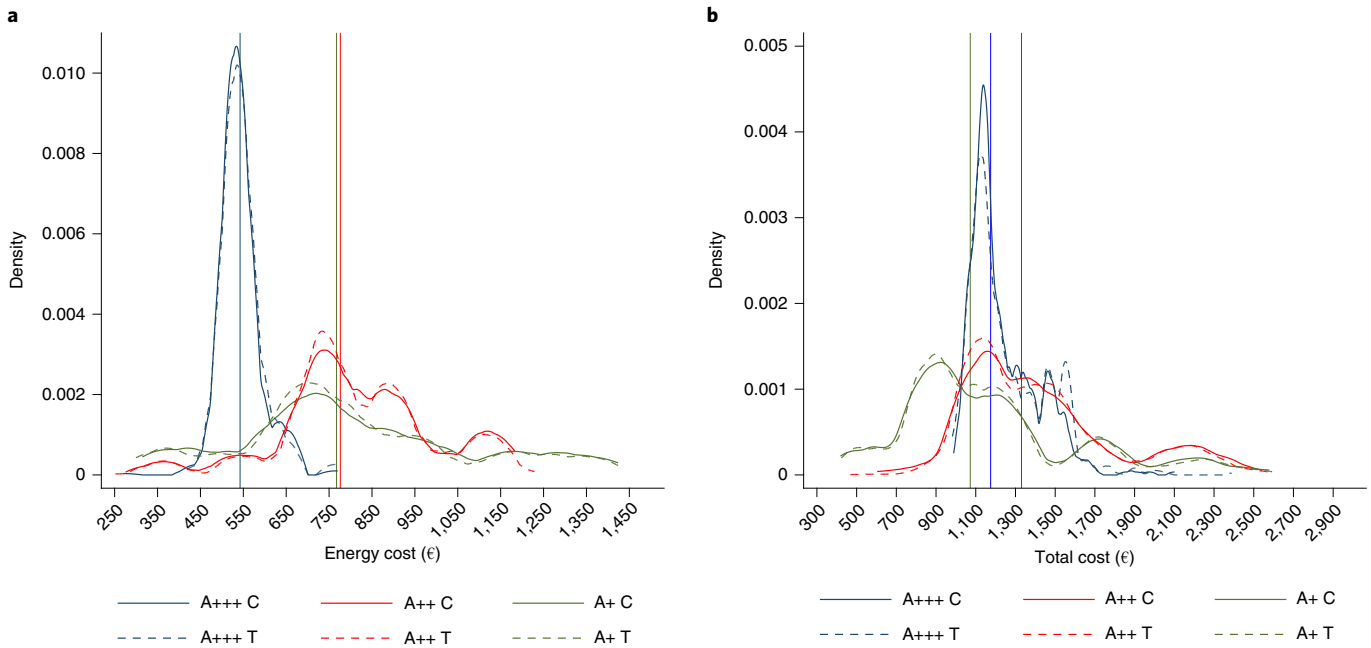

Fig. 2 | Distribution of lifetime energy cost and total cost of purchased refrigerators. a,**b**, The figure displays the kernel distribution of energy costs (**a**) and total costs (**b**) of purchased refrigerators ($n=7{,}545$), by treatment (C, control and T, treatment), for products in energy class A+++, A++ and A+. Vertical lines indicate the median values of energy costs (**a**) and total cost (**b**) of purchases in energy class A+++ (blue), A++ (maroon) and A+ (green) in the control group. The solid (dashed) lines depict the distributions of the control (treated) group.

is economically meaningful. For instance, the treatment effect on the likelihood that a customer buys an A+++ refrigerator is about as large as the impact of a €40 increase in the average daily price of A+++ refrigerators (column 5).

To understand why the treatment affects energy class but not energy cost, Fig. 2 displays the distribution of lifetime energy cost (Fig. 2a) and total cost (Fig. 2b) of purchases by energy class and treatment. The distribution of energy costs differs between the treated and control when we pool all the energy classes (Kolmogorov–Smirnov test, $P=0.054$), while median energy costs are the same (Wilcoxon rank-sum test, $P=0.389$). No differences between control and treated are also observed in the overall distribution of total costs, and in the distributions of energy and total costs within each class. These results indicate that the treatments affect the overall distribution of energy costs, without significantly increasing their median or average values.

The overlap between the distributions of energy costs of the three classes is greatest in the region ranging from the median of A+++ and the median of A++ for the control group, denoted by the blue and maroon vertical lines in the figure: within this region, a decrease in purchases of A+++ products and a corresponding increase in those of A+ and A++ ones is apparent. The shift away from A+++ and towards A++ and A+ also seems clear when considering total costs (Fig. 2b): again, differences in distributions by treatment are concentrated in the region where the overlap between the three distributions is greatest. We test this claim by evaluating treatment effects on the characteristics of purchased refrigerators whose energy cost lies between the median of A+++ and the median of A++ products bought in the control group: we find that treatment effects are larger in magnitude and more statistically significant within this region. The treatment leads to an increase in the energy costs of purchases (Supplementary Table 13, panel A, column 1, $\beta=5.936$, $P<0.1$), which is more than offset by the reduction in their price (column 2, $\beta=-25.64$, $P<0.05$), resulting in significantly lower total cost (column 3, $\beta=-19.41$, $P<0.1$). These results indicate that the treatment induces a shift in purchases from more expensive to cheaper products with lower total costs, particularly where energy and total costs overlap, and are therefore more directly comparable, across energy classes.

Treatment effect on search patterns

The results on purchases indicate that providing information on energy costs on top of the energy labels affects users' choice of products. We exploit available website navigation data to study whether these different choices result from different search patterns induced by the treatments. Overall, treated buyers view more pages and spend more time searching (Table 2): the total number of pages viewed increases in the treatment group by 5.4% when we include cart pages (column 1, $\beta=2.191$, $P<0.1$), and by 6.9% when we consider only product pages (column 2, $\beta=1.614$, $P<0.1$). Such an overall effect is not driven by any particular energy class (Supplementary Table 14). The overall increase in search time, by 3 minutes or 6.4% (column 3, $\beta=187.638$, $P<0.05$), is driven by a 10.4% increase in time spent viewing A+ products (column 6, $\beta=100.880$, $P<0.05$). Product prices appear less relevant for search than for purchase decisions. We do not observe significantly different effects between the 1- and 15-year treatments on overall search outcomes, although point estimates relative to the control are larger and more statistically significant in the latter (Supplementary Table 15). These results are qualitatively robust to different specifications and definitions of the sample and of the treatment indicator, to deal with users exposed to multiple treatments or making multiple purchases (Supplementary Tables 16–22); as well as when we consider the full sample of users on the website (Supplementary Table 23).

The distributions of energy and total costs of viewed products by treatment and energy class indicate that users search over a wide range of products before selecting what to buy. The treatments cause a shift in product views towards refrigerators with lower total costs (Fig. 3). Energy costs of viewed products are on average €3 lower in the treatment group (two-sided t-test, $P=0.000$): this overall dif-

Table 2 | Treatment effects on buyers' search

Dependent variable	Number of pages viewed		Number of seconds spent on pages (cart and product)			
	Product and cart pages	Product pages	All	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	2.191*	1.614*	187.638**	−24.570	99.692	100.880**
	(1.171)	(0.913)	(88.984)	(44.922)	(61.074)	(45.778)
Average daily price A+++	1.049	0.775	−10.644	−84.513	16.802	65.629
	(1.512)	(1.294)	(124.032)	(51.983)	(96.158)	(55.332)
Average daily price A++	0.584	0.188	−31.972	−18.556	−85.245	46.684
	(1.833)	(1.578)	(152.575)	(72.182)	(102.417)	(76.770)
Average daily price A+	3.193	2.738	405.786**	148.728*	195.997	28.741
	(2.304)	(1.911)	(188.197)	(89.995)	(127.247)	(93.757)
Observations	7,635	7,635	7,635	7,635	7,635	7,635
R-squared	0.158	0.164	0.183	0.202	0.152	0.154
Mean control	40.62	23.49	2,926	614.5	1,263	969

Note that OLS regressions are used. Robust standard errors are in parentheses. All regressions control for week- and municipality-fixed effects. Treat is a dummy equal to one for users whose modal treatment is one of the two energy cost information treatments. Average daily prices indicate the average price of refrigerators in the different energy classes on the day of the purchase: the coefficients on these variables capture the impact of a €100 increase in prices. The table considers the sample of buyers and reports the mean of the dependent variable in the control group. No adjustments were made for multiple comparisons. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

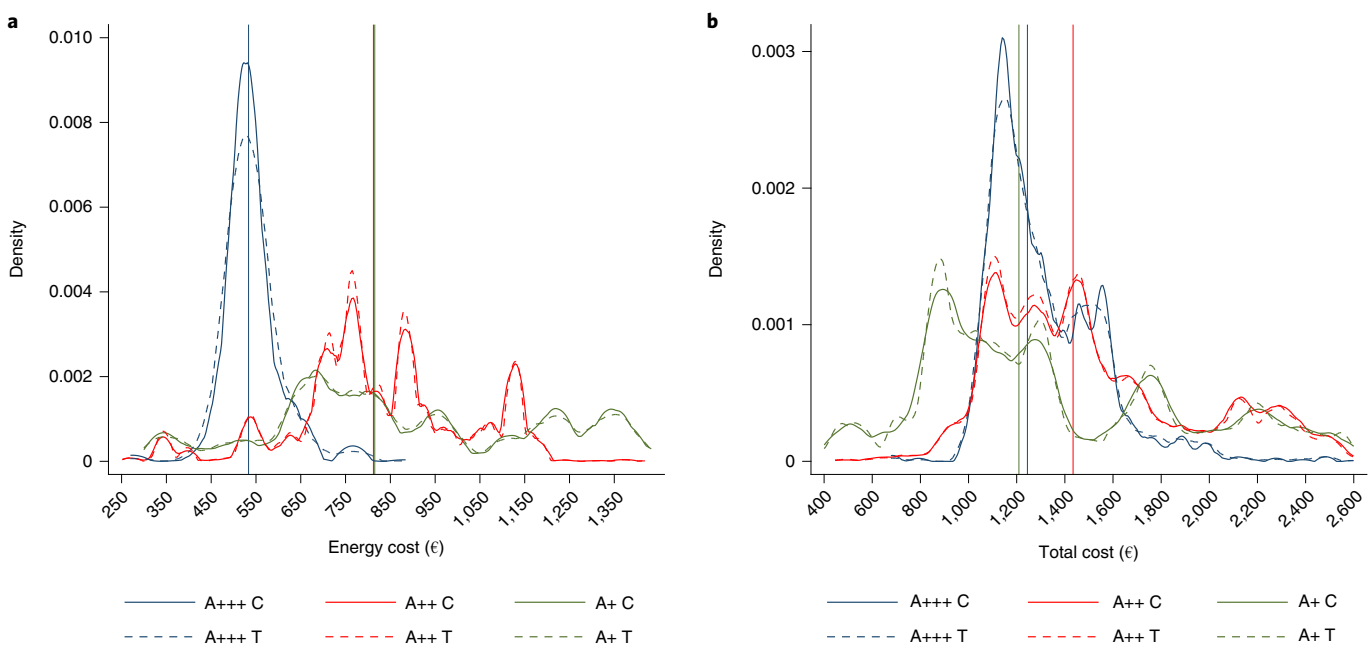

Fig. 3 | Distribution of lifetime energy cost and total cost of viewed refrigerators. a,**b**, The figure displays the kernel distribution of energy costs (**a**) and total costs (**b**) of viewed refrigerators ($n=956{,}670$), by treatment, for products in energy class A+++ or above, A++ and A+ or below. Vertical lines indicate the median values of energy costs (**a**) and total cost (**b**) of viewed products in energy class A+++ or above (blue), A++ (maroon) and A+ or below (green) in the control group. The sample consists of all users ($n=126{,}614$).

ference being driven by products in the A++ ($P=0.000$) and A+ ($P=0.000$) energy classes. Their distribution differs by treatment both overall (Kolmogorov–Smirnov test, $P=0.000$) and within each energy class (Kolmogorov–Smirnov $P=0.004$ for A+++ and $P=0.000$ for A++ and A+), as does their median (Wilcoxon rank-sum tests, $P=0.000$ overall and for A++ and A+). The same holds for the total cost of viewed products, whose median is lower overall and within each class in the treatment group (Wilcoxon rank-sum tests, all $P=0.000$), and whose distribution is also significantly different by treatment, both overall and within each energy class (Kolmogorov–Smirnov tests, all $P=0.000$). Therefore, the treatment enables users to identify, and focus attention on, products with lower total and energy costs rather than top-ranked ones in terms of energy class.

Next, we examine how the characteristics of products viewed change by treatment over the search process, by interacting the treatment indicator with a continuous variable capturing products' viewing order (Table 3). Treatment does not affect the characteris-

Table 3 | Viewed products' characteristics by treatment and viewing order

Dependent variable	Lifetime energy cost (€)	Price (€)	Total cost (€)	A+++	A++	A+
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−1.266	4.435	2.791	0.001	0.003	−0.004
	(1.923)	(3.698)	(4.948)	(0.002)	(0.003)	(0.003)
Product viewing order	1.270***	4.296***	5.438***	0.003***	0.003***	−0.006***
	(0.297)	(0.583)	(0.784)	(0.000)	(0.000)	(0.000)
Treat × viewing order	−0.274	−2.082***	−2.368**	−0.000	−0.001**	0.001***
	(0.358)	(0.699)	(0.942)	(0.000)	(0.000)	(0.000)
Observations	442,502	419,159	419,159	442,502	442,502	442,502
R-squared	0.036	0.033	0.038	0.024	0.015	0.023
Mean dependent variable control	806.1	717.2	1,523	0.146	0.395	0.451

Note that OLS regressions are shown. Standard errors are clustered at the individual level. 'Treat' is a dummy equal to one for users whose modal treatment is one of the two energy cost information treatments. 'Product viewing order' captures the order in which a user views a product. The sample includes all users and considers up to the 26th product viewed, that is, the 99th percentile of the number of products viewed by all users. Regressions include week- and municipality-fixed effects. The table reports the mean of the dependent variable in the control group. No adjustments were made for multiple comparisons. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

tics of the first product viewed. As products' viewing order increases, users view refrigerators with higher lifetime energy cost, price and, as a result, total cost; users are more likely to view A++ and A+++ refrigerators and less likely to view A+ ones. This seeming contradiction, that is, that increases in energy costs and efficiency class of viewed products go hand-in-hand, confirms that energy class is an imprecise indicator of energy cost. It suggests that users may underestimate the energy consumption of products in high-efficiency classes and of less efficient products within each class.

The treatment partially offsets these tendencies, significantly so for price (column 2, $\beta=-2.082$, $P<0.001$); total cost (column 3, $\beta=-2.368$, $P<0.05$) and for the likelihood to view A++ (column 5, $\beta=-0.001$, $P<0.05$) and A+ (column 6, $\beta=0.001$, $P<0.01$) products. These effects do not appear to differ by level of aggregation of the energy costs (Supplementary Table 24). We represent these patterns graphically, replacing linear viewing order with viewing-order fixed effects and plotting them by treatment group (Supplementary Fig. 4). They are qualitatively robust to restricting attention to buyers and users exposed to a single treatment (Supplementary Tables 25 and 26). These results are also confirmed when we examine how viewed products' characteristics affect search behaviour, by treatment; treated buyers spend more time on product pages of A+ refrigerators, and relatively less time on those of A++ and A+++ refrigerators than buyers in the control group, while the treatment has no differential effect on the end of the search process for buyers depending on refrigerators' characteristics (Supplementary Table 27). On the contrary, the treatments do not change the likelihood to end the search or the time spent on a page depending on the product's relative energy consumption within each class (Supplementary Table 28). In other words, the treatments primarily lead users to compare products across, rather than within, energy classes.

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, directs purchases towards cheaper products in lower-efficiency classes, but with similar energy cost and total costs. This result is consistent with consumers' overweighting energy class in their purchase decisions when energy cost information is not provided in a readily accessible form, and with energy class being an imperfect proxy of energy costs. Furthermore, the finding that treatments increase search time on low energy-efficiency class products supports the claim that energy cost information draws users' attention to the total cost of products and suggests that energy classes allow prospective buyers to save on cognitive effort.

Given the statistically insignificant impact of providing simple but accurate cost information on the total cost of purchases, and the added cognitive and time costs of a more elaborate search process, it is unclear whether the provision of energy cost information improves customers' welfare. Nonetheless, the fact that the EU energy label allows for substantial overlap in energy costs between similar products in different energy classes raises the question of whether the provision of energy cost information within the EU label may improve its transparency. The recent reform of the EU label has changed the notation of energy classes back to grades A to G, but not the way in which classes are calculated. This issue is not restricted to the European case, as labels in several other countries rely on similar rules to compute energy-efficiency classes. Moreover, as energy costs might temporarily increase as part of the energy transition, the fact that energy classes draw consumers' attention away from energy costs may have unintended social and economic implications and might delay the uptake of energy-efficient products.

Methods

Ethics statement. Ethical approval for the use of the data that support the findings of this study was granted by the Institutional Review Board at Politecnico di Milano (approval number 19924). The participants did not provide informed consent as the experiment occurred on the company's website, within the standard commercial activities of the company.

Sample. Our sample comprises customers who viewed a refrigerator from the desktop version of a major Italian online retailer's website between 1 June and 16 October 2018. We identified 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 assigned to the same registered customer ID all observations with the same cookie-based ID and missing registration ID: these were pages that a registered user viewed without being logged in. We identified the remaining customers, that is, customers who never register or log in, through their cookie-based ID. This may leave room for two types of error: first, we may have assigned different IDs to the same customer if they never logged in and cleared the cookies or used other browsers or computers; second, we may have assigned the same ID to different customers if they never logged in and used the same shared computer and browser. However, we have no reason to think that these cases may occur differentially across treatments. We obtained a sample of 126,614 customers who viewed a refrigerator page over the study period.

Treatments. The English (Italian) versions of the treatment messages are: (1) for the 1-year treatment, 'You spend €X on energy in 1 year.' (Spendi €X di energia in

1 anno.) and (2) for the 15-year treatment, 'You spend €X on energy in 15 years.' (Spendi €X di energia in 15 anni.). Supplementary Figs. 1 and 2 display the original Italian version of the treatment visualization on the retailer's listing and product pages, respectively. The figures omit the product's brand, models and the retailer's name for confidentiality.

In addition, each time the customer clicked on the energy cost information sentence, a pop-up window explained the sources of data for the kWh unit cost and refrigerator lifetime. Since only 0.7% of users (1.7% of buyers) clicked to open the pop-up window, we did not analyse this feature.

Treatment assignment. 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 the three treatments. Therefore, as long as a customer did not clear cookies, they would be exposed to the same treatment on all 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, indicates that the same customer could be exposed to multiple treatments if they viewed refrigerators from different computers or laptops without being registered or logged in. Indeed, 7,187 customers in our sample were assigned to multiple treatments; of them, 1,313 made a purchase. We define exposure to multiple treatments conservatively, that is, regardless of whether it occurred before or after buyers made a purchase, also given the presence in our data of buyers making multiple purchases ($n=281$). Users exposed to multiple treatments are more likely to make a purchase (18 versus 5%, two-sided t-test, $P=0.000$), since prospective buyers search more intensively, possibly on multiple devices. Supplementary Table 29 shows the different treatment combinations for users exposed to more than one treatment. Treatment combination is defined as the sequence of unique treatments a user is exposed to, that is, it does not consider repeated exposure to the same treatment. Supplementary Table 30 shows the variation between initial treatment and treatment at the time of purchase for buyers: the two distributions are significantly different (Wilcoxon sign-rank test, $P=0.029$). However, the likelihood of being exposed to multiple treatments does not depend on the initial treatment assignment (Supplementary Table 31). Our main specifications include these users and assign them to the modal treatment, but our results are qualitatively robust to their exclusion from the sample (Supplementary Tables 6 and 7 and 17 and 18); to restricting the sample only to these users (Supplementary Tables 8 and 19); to defining treatment as the initial treatment (Supplementary Tables 10 and 21) or, for buyers, as the treatment at the time of purchase (Supplementary Tables 11 and 22).

Supplementary Table 1 reports summary statistics of customers' characteristics, which are only available at the municipal level, and shows that they are balanced across the modal treatments. On the basis of 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 higher shares of both high school and university graduates, and higher income levels than national averages[29], consistent with the profile of buyers on online markets[30]. The lack of individual-level demographic characteristics is a limitation of our data, affecting the assessment of balance by treatment, as municipal-level data may suffer from aggregation bias.

Multiple purchases. A total of 281 users made multiple purchases. Multiple purchases are predominantly cases of orders cancelled and then re-issued, for instance, following a payment failure due to insufficient funds on a pre-paid card. In these cases, we kept the user's last purchase, so our data comprise only one refrigerator purchase per user. Our results are robust to excluding these customers (Supplementary Tables 5, 7, 16 and 18). Ruling out multiple treatments and multiple purchases results in a sample of 119,252 users and 7,354 purchases.

Energy cost calculation. 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 ARERA website[31]. We selected the latest available figure of the residential cost of a kWh, equal to €0.1998 in the second quarter of 2018, and computed all energy usage costs applying this same unit cost, undiscounted, to all future periods. The fact that the Italian electricity market was predominantly regulated during the study period and that the price of a kWh in 2018 varied at most by €0.015 relative to the figure we use in the energy cost calculations minimizes concerns over the accuracy of the energy cost information due to variations over space and time in energy prices.

The average lifetime of a refrigerator was set at 15 years, on the basis of engineering estimates available from the National Agency for New Technologies, Energy and Sustainable Development (ENEA) website[24]. When computing lifetime energy costs, we 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. 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.

Estimation of the implied discount rate and of discounted energy costs. Exploiting the daily variation in prices and customers' navigation history, we estimate an implied discount rate equal to 5–8%; this is smaller than the elicitation in another study[32]. The estimation framework is analogous to the attention weight models in refs. [4,5,32,33]. The estimation procedure focuses on the treated consumers and relies on the following assumptions:

(1) Consumers are fully informed about the energy cost and fully consider this information.
(2) Consumers make energy-saving calculations using a constant discounting model with an annual discount rate r.
(3) Consumers take 15 years as the expected life duration.
(4) On the basis of the above assumptions, a consumer in the 1-year treatment will take $\text{price} + f\sum_{t=1}^{15} e^{-rt}$ as the lifetime cost of a fridge, where price is the purchasing price 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 $\text{price} + \frac{c}{15}\sum_{t=1}^{15} e^{-rt}$ as the lifetime cost of a fridge, where price is the purchasing price 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 to the 15-year treatment.

The analysis uses 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 we have one observation for each product-price combination viewed by a customer. The search outcomes support the latter assumption. We take the simple linear model:

$$\text{BuyFridge}_{ijt} = \beta_1 + \beta_2\text{Price}_{tj} + \beta_3 f_j + \gamma_t + b_j + t_j + \delta_i + \varepsilon_{ijt} \quad (1)$$

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 annual 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 and so on), two important features of the product. δ_i are individual fixed effects. The coefficients β_2 and β_3 represent 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-effects logit model where the left-hand side of the equation becomes a latent variable representing the use of purchasing the fridge. Supplementary Table 32 reports the regression results, while Supplementary Table 3 shows how our treatment effects are affected by the discount rate applied to energy costs.

Products. The study encompasses free-standing refrigerators, excluding minibars, available for delivery during the time of the study. About 2000 products met these criteria in the online retailer's catalogue and accounted for 81.65% of refrigerators' sales in 2018. Therefore, they were the most common type of refrigerator sold by our partner retailer over the year of the study. A few considerations determined the exclusion by the retailer of built-in refrigerators from the study. First, when a built-in refrigerator is bought to replace an older one, its choice is predominantly driven by size, as the product has to fit within a predetermined space: often, to minimize the risk of the new refrigerator not fitting, buyers avoid switching brand. Second, when a built-in refrigerator is bought for a new kitchen, the kitchen supplier typically provides the appliances and installs them. Third, built-in refrigerators are harder to install, and are therefore more likely to be purchased from physical stores that also provide installation services. All these considerations constrain customers' choice when buying a built-in refrigerator, thus reducing the treatment's expected impact on the features of purchases within this class of products.

In the paper, we mention the three energy classes, A+++, A++ and A+, to which most refrigerators in our data belong. However, at the time of the study, A+++ minus 10% and A+++ minus 20% refrigerators were also available, 10 and 20%, respectively, more efficient than the average A+++ refrigerator. The catalogue also included refrigerators in class A, although they could not be sold by law. Given the low frequency of these instances, which account for less than 0.5% of the products on the catalogue and 27 purchases (four purchases in each of the A+++ −10% and A+++ −20% classes, and 19 purchases of A class), we pool A+++ minus 10% and 20% classes with A+++ and A class with A+ products, and refer to them in the text as A+++ and A+ refrigerators, respectively.

Data. The main data source 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 include information on the municipality of the user's IP address and details on the page visited. 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 favourites 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 favourites, overall and by energy class. 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.

We combine navigation data with data from the product catalogue, containing information on each product: description, brand, category (for example, one door, fridge-freezer, three doors and so on), size in litres, energy class and yearly consumption in kWh. We also add 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 1 June to 16 October, plus its shipping price and information on any active promotion on the product on that date. 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, resulting in multiple price updates 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.

Finally, we have municipal-level data on population, income, education and other socioeconomic characteristics[29], 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 121,527 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.

Treatment impact. 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, on the characteristics of refrigerators bought and on overall search behaviour, that is the number of pages and products viewed and search time. We address these questions by estimating the following linear regression model, with robust standard errors:

$$y_{itm} = \beta_1 + \beta_2 \mathrm{Treat}_i + \beta_3 \mathrm{PriceA3}_t + \beta_4 \mathrm{PriceA2}_t + \beta_5 \mathrm{PriceA1}_t + \gamma_t + \delta_m + \varepsilon_{it} \quad (2)$$

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; $\mathrm{PriceA3}_t$, $\mathrm{PriceA2}_t$ and $\mathrm{PriceA1}_t$ 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 compare treated and control customers, or distinguish between the 1- 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 whether they registered with the website or bought a refrigerator. When analysing the characteristics of purchases and overall search behaviour, we focus on the subsample of customers making a purchase. Supplementary Table 27 reports treatment effects on overall search behaviour for the full sample of users, while Supplementary Tables 5 and 18 report the effect of each treatment separately.

Analysis of the search process. We study how the treatment affects users' behaviour over the search process using the full navigation data. For this analysis, we consider the full sample of users: only product pages, that is, we exclude listing and cart pages, and the first 26 products viewed. This corresponds to the 99th percentile of the distribution of the total number of products viewed by users (Supplementary Fig. 5).

We estimate the following linear regression model, with standard errors clustered at the individual level:

$$y_{iktm} = \beta_1 + \beta_2 \mathrm{Treat}_i + \beta_3 \mathrm{Ord}_k + \beta_4 \mathrm{Treat}_i \times \mathrm{Ord}_k + \gamma_t + \delta_m + \varepsilon_{iktm} \quad (3)$$

where y_{iktm} is a feature of the kth product viewed by user i, who visited the website's refrigerator pages for the first time at time t and navigated the website primarily from municipality m; Treat_i is treatment status; Ord_k denotes the product's viewing order through a linear viewing order trend; $\mathrm{Treat}_i \times \mathrm{Ord}_k$ is the interaction between the treatment and the product's viewing order; and γ_t and δ_m are week and municipality-fixed effects. Supplementary Table 24 examines each treatment's effect separately; Supplementary Tables 25 and 26 consider only users exposed to a single treatment and buyers, respectively. We run equation (3), replacing linear viewing order with viewing-order fixed effects, and plot marginal effects by treatment status (Supplementary Fig. 4).

Besides examining whether viewed products' characteristics change by treatment along the search process, we study whether users' decision to end the search at a product page and the time spent by users on a product page are affected by the viewed product's characteristics differently depending on the treatment. This analysis also focuses on the first 26 product pages viewed and considers all users, but distinguishes between buyers and non-buyers, as ending the search process results in very different outcomes for the two groups. We estimate the following equation, with standard errors clustered at the individual level:

$$y_{iktm} = \beta_1 + \beta_2 \mathrm{Treat}_i + \beta_3 \mathrm{Char}_k + \beta_4 \mathrm{Treat}_i \times \mathrm{Char}_k + X_k + \mathrm{Ord}_k + \gamma_t + \delta_m + \varepsilon_{iktm} \quad (4)$$

where y_{iktm} is a dummy equal to 1 if product k is the last product viewed by user i, or the time spent by user i on product k's page; Treat_i is treatment status; Char_k is a feature of product k, such as its price or energy class; $\mathrm{Treat}_i \times \mathrm{Char}_k$ is their interaction; X_k are other features of product k; Ord_k are product viewing-order fixed effects and γ_t and δ_m are time and location fixed effects. We study the end of the search using a complementary log–log survival model, where location fixed effects are region fixed effects and a province city dummy. We study search time using linear regression with municipality-fixed effects. Results are reported in Supplementary Table 27.

Pre-registration. This study is registered in the American Economic Association (AEA) RCT Registry (AEARCTR-0003939)[34]. 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 primarily to include 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 Supplementary Tables 33–35: its results are robust to alternative specifications, including seemingly unrelated regressions, to deal with the correlation between the outcome variables in regressions of treatment effects on purchases' characteristics. Supplementary Tables 9 and 20 instead show that our main results are robust to omitting price controls from equation (2).

In addition, the analysis reported in this section differs from what was promised in the PAP in the following ways. First, 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. Second, the number of sales reported in the PAP differs from the one used in the analysis, because, at the time of writing the PAP, we did not know how many of the total sales, reported by the online retailer over the study period, concerned product categories excluded from the experiment (that is, built-in refrigerators and minibars). Third, in the regressions we do not cluster standard errors by municipality, as promised in the PAP, because clustering is not correct in the presence of individual-level randomization of treatment. We instead control for municipality-fixed effects.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The data that support the findings of this study are proprietary data of the retailer and cannot be shared publicly. To enquire about access to the proprietary data in a synthetic format, please contact G.dA. Source data are provided with this paper.

Code availability

The code is available on the Open Science Framework at https://osf.io/cxnyu/

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Author contributions

G.dA., Y.G. and M.T. conceived and designed the experiment. G.dA. oversaw the implementation of the experiment and analysed the data. G.dA. and Y.G. contributed the analysis tools. G.dA., Y.G. and M.T. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41560-022-01002-z.

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data was collected by the online retailer with whom we conducted the experiment. Data on purchasing and navigation decisions were tracked and collected by the company-
Data analysis	Data analysis was carried out with Stata 15. The software is publicly available at: https://osf.io/cxnyu/

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Data, which is quantitative, includes real purchases of refrigerators and navigation data on line on the retailer website. This study is registered in the AEA RCT Registry (AEARCTR-0003939) and received IRB approval from the Ethics Committee at Politecnico di Milano (ID 19924). We follow the registered Pre analysis plan identification strategy with one exception, which is clarified in the manuscript.
Research sample	The sample includes about 128.000 customers of the on line retail company we partnered with. all sample descriptives are in the manuscript. the sample is representative of the population of company customers, not of the general population. The study sample are the customers of the company we carried out the experiment with, which is (or used to be) the largest online retailer of refrigerators serving in particular Northern Italy.
Sampling strategy	Study sample was randomized to control and 2 treatment arms. The sample involved all the company customer base who made purchases or searched for refrigerators during the study period
Data collection	Data was collected by the company through their standard procedures, since it involves records of purchases and website navigations which the company tracks for its operations. The company used internal procedures for recording the data of their customers. The researchers designed the study, so were not blinded. The customers were blinded.
Timing	between June 1st and October 16th, 2018
Data exclusions	7k customers out of 128k were assigned to multiple treatments due to multiple IP log ins. we assign these customers to the modal treatment and test the robustness of our results to their exclusion from the sample
Non-participation	Participants enrolled voluntary but without knowing they were part of an the experiment by viewing or purchasing the company's products online. Thus no participant declined participation
Randomization	Customers were randomized at the IP levels into 3 groups (1 control, 2 treatment arms) or around 40k customers each.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☐	☒ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	The sample involves about 126k customers viewing and purchasing products on the company webpage. We don't have individual-level information on users, except for their IP address.
Recruitment	The experiment was carried out by the on line retailer who created 3 different versions of the website and randomized their appearance. No recruitment was involved, as customers voluntary went on the seller webpage.

Ethics oversight	Politecnico di Milano ethics board approved the experiment. The participants did not provide informed consent as the experiment occured on the company's website, within the standard commercial activities of the company.

Note that full information on the approval of the study protocol must also be provided in the manuscript.