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Consumer Inattention and Decision Heuristics: The Causal Effects of Energy Label Elements

Energy labels have been introduced in many countries to make consumers more attentive to energy use in purchase decisions of durables. Despite their wide application, however, little is known about the effects of specific label designs. In this paper, we explore how energy labels can help to address inattention of consumers to energy efficiency. Our analysis is based on a (randomized controlled) discrete choice experiment among about 5,000 households in which we implement treatments that vary the label design. We find that supplementing the label with annual cost information increases attention to operating cost and promotes the choice of durables with higher energy efficiency. Moreover, simplifying the label has similar positive effects, most notably for individuals with low education. Finally, we show that a substantial share of individuals employ decision heuristics, focusing primarily on efficiency classes while neglecting more detailed information on energy consumption.

Keywords: Environmental certification, discrete choice experiment, energy efficiency, energy-using durables.

JEL codes: D03, D12, D83, Q48, Q50.

1. Introduction

Research from behavioral economics and psychology demonstrates that consumers are attentive to salient attributes of products, while neglecting more opaque value components, such as sales taxes or shipping cost (see Chetty et al., 2009; Hossain and Morgan, 2006). In the context of energy efficiency, investments in energy-using durables typically involve a trade-off between clearly visible investment costs and more opaque operating costs. Consequently, consumers seem to be inattentive to operating costs, leading to an insufficient consideration of energy efficiency in purchase decisions (see e.g. Allcott and Taubinsky, 2015). Accordingly, inattention to energy costs has been proposed as an explanation for the low tendency of consumers to invest in cost-effective efficiency technologies (e.g. Allcott, 2011), which is commonly referred to as “energy efficiency gap” (Jaffe and Stavins, 1994).

Inattention can have adverse welfare implications if it triggers mis-optimizations of consumers that lead to differences between experienced utility and its ex-ante evaluation – a situation described as an “internality” (Allcott et al., 2014). Besides eliminating internalities, removing inattention may be helpful to reduce negative externalities associated with the consumption of energy from fossil fuels, such as carbon emissions. As a particularly important instrument to tap this potential, energy labels for energy-using durables have been introduced all around the world. Presumably the two most established energy label schemes originate from the EU and the US, but similar schemes are used in many countries, such as China or India.

In this paper, we uncover how energy labels can mitigate consumers’ inattention to energy efficiency. We conduct a discrete choice experiment that is framed as the purchase decision on refrigerators among 5,000 households and identify the causal effects of label elements by varying the design of the efficiency label. We implement two treatments: First, we add further elements to the label to increase the number of attributes that compete for attention. Second, we include annual electricity cost information in the label with the idea of facilitating the evaluation of operating costs and thus to increase its salience. Furthermore, we construct specific choice sets to isolate potential mechanisms through which our treatments work. One choice set focuses on a situation where efficiency class differences are absent to identify how attention to operating cost is affected. Another choice set takes advantage of discontinuities in the assignment of efficiency classes: We present appliances that hardly differ in electricity usage, but fall into different efficiency classes. This allows us to separate the effects of these attributes.

Previous research has mainly focused on the US EnergyGuide and Energy Star schemes. Newell and Siikamäki (2014), for instance, investigate the impact of different label elements on the willingness to pay for reductions in operating costs. They find that both the inclusion of annual electricity cost and meaningful energy efficiency ratings in the label lead to a higher willingness to pay. Using transaction data on refrigerators, Houde (2014b) estimates a latent class model on information search and energy efficiency investments allowing for three types of consumers: some consumers rely predominantly on the coarse quality signal of the Energy Star, some rely on electricity costs as an indicator of energy efficiency, while others do not consider energy efficiency information at all. More broadly, by showing that information provision raises the willingness to pay for energy efficient light bulbs, Allcott and Taubinsky (2015) find experimental evidence for inattention.

In contrast to the US, research on the EU labeling scheme is scarce. This is particularly

regrettable, because it differs substantially from the US scheme, so that results from the US may not be transferable. Most notably, rather than providing detailed cost information, the EU label includes energy efficiency classes ranging from D (least efficient) to A+++ (most efficient). Furthermore, the US scheme allows to complement the mandatory EnergyGuide label with the voluntary Energy Star label if the energy efficiency of the appliance passes a predefined threshold, while displaying all elements of the EU label is mandatory.

Our results show that additional cost information boosts the effectiveness of the EU label in guiding consumers to more energy efficient appliances. The analysis indicates that the provision of cost information draws attention to operating cost. This effect is most pronounced when household income is low. Furthermore, we find that increased complexity of the label raises inattention to operating cost for individuals with low education levels. Lastly, our results show that a large share of the individuals employ a simplifying decision heuristic by focusing predominantly on efficiency classes, while neglecting the information about the actual energy consumption. Interestingly, the provision of annual electricity cost information decreases the share of individuals that rely on efficiency classes, which documents a substitution effect between the two elements of energy labels.

We proceed as follows: Section 2 introduces the EU label and the market for refrigerators, while Section 3 presents the conceptual model and our hypotheses. In Section 4 we discuss the experimental design and the underlying data, before Section 5 describes the empirical strategy and shows the results. Section 6 summarizes and concludes.

2. EU label and the market for refrigerators

The labeling scheme in the European Union is mandatory, i.e. whenever household appliances are offered for sale, the label on energy consumption has to be displayed. By making energy efficiency information more accessible, the main purpose is to induce consumers to purchase more energy efficient appliances.

As visualized in Figure 1, the label for refrigerators displays annual electricity consumption, an energy efficiency class ranging from D (least efficient) to A+++ (most efficient) and further product features, such as the capacity of fresh food or frozen food compartments and the overall noise level. Due to the imposition of minimum standards via the Ecodesign Directives 2005/32/EC and 2009/125/EG, refrigerators that are less efficient than class A+ are banned

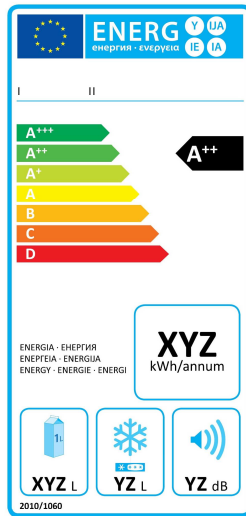


Figure 1: Example of the EU label for refrigerators

from the EU market since July 2012.

In principle, the assignment of efficiency classes follows directly from the energy consumption of the appliance for each category of refrigerators. Electricity consumption is translated into the Energy Efficiency Index (EEI) based on a formula that also accounts for some other product characteristics, such as its type and size.¹ Efficiency classes are then attributed to appliances depending on whether the EEI passes certain cutoff values. The consequence of such an assignment rule is that, at the cutoffs, marginal changes in electricity consumption lead to jumps in the efficiency class of the appliance. Finally, note that the efficiency classes do not carry additional information that is unknown to potential buyers, but merely aggregates already available product characteristics.

We now briefly discuss energy efficiency in the market for refrigerators. To investigate the distribution of energy efficiency in the market for refrigerators, we focus on Germany as it is the largest market in Europe. We have examined product data sheets from large online retailers for electric appliances and have calculated the EEI of the appliances. Figure 2 gives the frequencies of the EEI for refrigerators on the German market and illustrates that there is very strong bunching below the EEI values of 42 for A+, 33 for A++ and 22 for A+++ appliances.²

¹See EU Directive 2010/30/EU for the detailed calculation rule.

²The underlying data of this analysis stems from the product data sheets of all 109 refrigerators that in July 2015 were listed in at least one of the online catalogs of two of the largest German retailers for electric appliances, Media Markt (www.mediamarkt.de) and Saturn (www.saturn.de). Three appliances slightly exceed the legal cutoff for A+ appliances. This can be traced back to the fact that the threshold for A+ refrigerators was revised and reduced from 44 to 42 in July 2014 – a change that did not affect appliances that were already

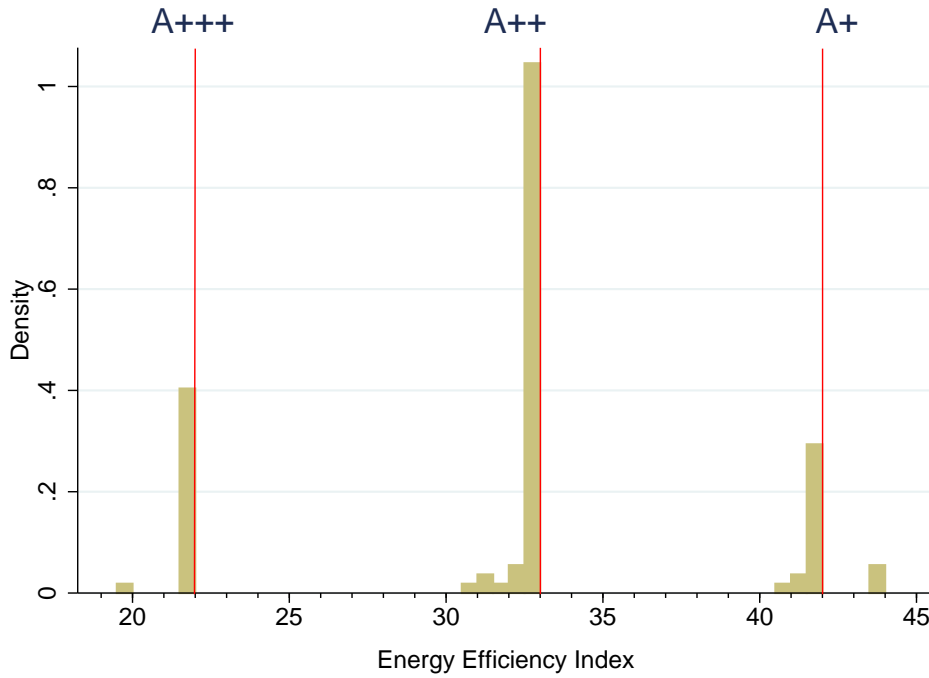


Figure 2: Energy Efficiency of Appliances on the Market

Interestingly, these values correspond exactly to the threshold values that are relevant for the respective efficiency classes.

This finding strongly indicates that producers of refrigerators respond strategically to the existence of efficiency classes by adjusting the energy efficiency of their appliances. This is interesting in at least two respects. First, our results for the mandatory EU label with its several efficiency classes are in line with the results from Houde’s (2014a) analysis for the US market that focuses on the voluntary Energy Star label. Houde finds strong bunching at the certification threshold for the Energy Star label and argues that the label allows producers to target consumers that value certification by offering energy-efficient appliances and increasing prices in response to the quality differentiation. Second, strategic efforts to reach a certain efficiency class are only profitable if consumers value efficiency classes per se, i.e. beyond the economic value of the underlying energy consumption – which is one of the hypotheses we analyze. Before, we develop the conceptual model and all hypotheses.

on the market.

3. Conceptual model and hypotheses

We motivate our hypotheses using a slight adaptation of Gerarden et al.’s (2015) conceptual model of investment decisions into energy efficiency. Consider the choice between two durable electricity-consuming goods A and B that are equal in any quality dimension, but differ in purchase costs and electricity consumption. Fully rational consumers evaluate the present value of costs (PVC) for each alternative $j \in \{A, B\}$ by:

$$PVC_j = K_j + O(E_j, P^E) \times D(r, T) + C, \quad (1)$$

where K_j represents equipment purchase cost, $O(E_j, P^E)$ denotes annual operating costs that depend on electricity consumption E_j of alternative j and the electricity price P^E , both assumed to be constant over time for the sake of simplicity. $D(r, T)$ stands for a discount factor that depends on the consumer’s discount rate r and expected lifetime T of the appliance, while C denotes any further costs that are assumed to be invariant across alternatives.

To fix ideas, let A denote the more energy efficient alternative with higher purchase cost but lower operating cost. Given cost-minimizing behavior, consumers choose the energy efficient alternative A if its PVC is smaller than the PVC of alternative B:

$$PVC_A - PVC_B = \Delta K + \Delta PVO < 0, \quad (2)$$

where ΔK corresponds to the difference in equipment purchase cost and ΔPVO denotes the difference in the present value of operating costs between alternative A and B, $\Delta PVO = \Delta O(E_A, E_B, P^E) \times D(r, T)$. Empirical investigations into an “energy paradox” (e.g. Allcott and Wozny, 2014; Hausman, 1979 and many others) have typically used such a cost-minimizing decision rule as a benchmark and found that consumers seem to underinvest in energy efficiency. In our case, this would imply that alternative B is chosen even though Inequality (2) would suggest otherwise.

The trade-off between capital and operating cost involves components that vary largely in visibility. While differences in purchase prices can readily be evaluated by comparing price tags, the PVO can be categorized as an “opaque information” (DellaVigna, 2009): its calculation requires that consumers consider the given consumption level and have beliefs over electricity prices as well as the lifespan of the appliance. Additionally, consumers are supposed to discount

future savings by a factor that reflects their inter-temporal preferences, which is also a non-trivial task. Hence, it is plausible that – at least some consumers – only partially process the PVO in their purchase decision. Research in behavioral economics has shown that choice situations that involve both visible and opaque value components can lead to inattention of consumers with respect to the opaque value component (DellaVigna, 2009). In this case, consumers decide based on the difference between perceived present values of costs (PPVC):

$$PPVC_A - PPVC_B = \Delta K + \theta(S, N)\Delta PVO, \quad (3)$$

where $\theta(S, N)$ is an attention parameter that captures the degree to which the opaque component of PPVC is considered in the decision rule. We follow DellaVigna (2009) to write θ as a function of the salience of the (opaque) present value of operating costs S and the number N of stimuli that compete for attention. Under inattention, i.e. $0 \leq \theta(S, N) < 1$, operating costs are considered only partly, which offers an explanation why the cost-effective investment into the energy efficient alternative A may not be realized.

Some energy labels, in particular the EU label, give consumers coarse information about the energy consumption in form of efficiency classes. Previous research has shown that consumers tend to use decision heuristics in order to simplify complex choice situations (see Lacetera et al., 2012, or DellaVigna, 2009, for a summary). Although efficiency classes provide no additional content beyond the coarse information on electricity consumption levels, they may be considered as they allow to employ energy efficiency information in decision making with a minimum of cognitive cost. Using such heuristics, consumers' evaluation of the alternatives reads as follows:

$$PPVC_A - PPVC_B = \Delta K + \theta(S, N)\Delta PVO + \tau(S, N)\Delta EC, \quad (4)$$

where $\Delta EC_{A,B}$ denotes the difference in efficiency classes between alternative A and B and $\tau(S, N)$ reflects the valuation of this difference.

Building on this conceptual model, we formulate hypotheses that will guide our empirical investigations. We first hypothesize that an increase in the salience of operating costs by the provision of annual electricity cost on an energy label increases the probability P_A of choosing the more energy efficient appliance: $\partial P_A / \partial S > 0$ (*cost hypothesis*). Furthermore, we anticipate that a label with more competing stimuli N , i.e. more attributes that are not related to electricity consumption, leads to less frequent choices of the energy efficient appliance, so that $\partial P_A / \partial N < 0$

(*stimuli hypothesis*). For instance, some of the multiple elements of the EU energy label are not related to energy consumption, such as the noise level of the appliance. Next, our *heuristics hypothesis* claims that a large share of consumers employs decision heuristics based on efficiency class differences, i.e. consumers consider the coarse information of efficiency classes but ignore the given information about actual energy consumption. Hence, we expect the valuation of class differences to be positive, i.e. $\tau(s, N) > 0$.

As soon as efficiency class differences have a value on its own, i.e. $\tau(S, N) > 0$, the salience of operating cost S as well as the number of competing stimuli N can work through two channels: they can influence both attention to operating cost θ and the valuation of efficiency class differences τ . In our *ambiguity hypothesis*, we expect that both channels work in opposite directions. As psychological evidence suggest, we assume – analogously to DellaVigna (2009) – that the attention θ is increasing in the salience of operating cost information, $\partial\theta/\partial S > 0$, and decreasing in the number of competing stimuli, $\partial\theta/\partial N < 0$. In contrast, we expect that the valuation of class differences decreases in the salience of operating cost, $\partial\tau/\partial S < 0$. This corresponds to an information substitution effect between the efficiency classes and the provision of annual electricity costs (as suggested by Houde, 2014b). Furthermore, we anticipate that consumers rely more strongly on the simplifying decision heuristics in a cognitively demanding environment, i.e. the more competing stimuli, the higher the valuation of efficiency class differences so that $\partial\tau/\partial N > 0$.

4. Experimental design and data

To test our hypotheses, we conduct a randomized controlled trial within a representative survey. Specifically, we design a discrete choice experiment, where individuals repeatedly choose among two refrigerators that differ in purchase prices and electricity consumption levels. Our focus on refrigerators is particularly warranted as penetration rates reach close to 100 % in almost all EU member states (Bertoldi et al., 2012) and – in contrast to appliances such as dryer or washing machines – electricity consumption is largely independent of usage patterns.

We have randomly assigned each household into one of three groups. Households in the control group C serve as a baseline and receive information based upon a simplified version of the EU label, solely including information on annual electricity consumption and the EU efficiency class (Figure 3). In treatment group T_S , we increase the salience S of operating cost

by introducing an additional label element on annual electricity costs that we calculate using average electricity prices in Germany. In treatment group T_N , we complement the simplified version of the label by all remaining attributes of the original EU label and a picture of the refrigerator. As the sole purpose of this treatment is to increase the number of competing stimuli N , we take care to not introduce differences in the levels of the additional attributes. Hence, we only marginally vary compartment sizes and noise levels, as illustrated by Table 1. Furthermore, we use pictures from advertisements of the same refrigerator model that vary only in their food contents.³ The additional information is attributed to the choice sets in a random manner to avoid systematic confounding.

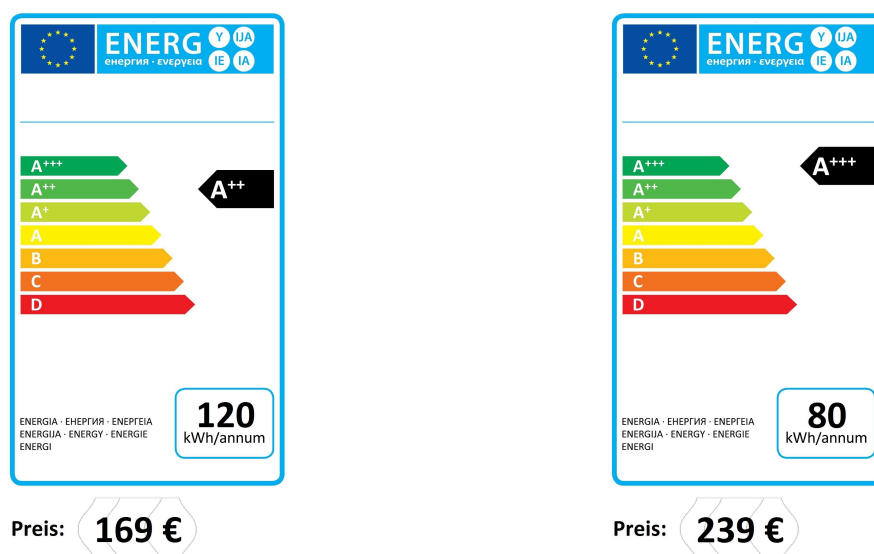


Figure 3: Illustration of the Binary Choice Set I presented to Individuals of the Control Group who are requested to choose between Alternative A (lefthand side) and Alternative B (righthand side)

To construct realistic choice sets, we examine product catalogs of two large German retailers and determine the range of purchase prices and electricity consumption levels on the market. For that purpose, we consider combined refrigerators and freezers with small to medium cooling compartment sizes (100-150 l) and freezer compartment sizes (12-18 l), as they form a homogeneous appliance class and represent a considerable share of the market.⁴ We use binary choice sets as they allow to estimate the causal effect of the treatments with a minimum of distributional assumptions (see e.g. Angrist and Pischke, 2009).

As visualized in Table 1, choice sets I and II correspond to a situation in which we expect a

³The pictures of the refrigerators are presented in Appendix XY.

⁴The online search in the product line of the retailers *Media Markt* and *Saturn* reveals a market share of roughly 20 %.

Table 1: Overview on our Choice Sets presented to the Control Group C , the Treatment Group T_C and the Treatment Group T_N , respectively

Choice Set	Alternative	Purchase Price	Electricity Consumption	Efficiency Label	Operating Cost	Cooling Compartment	Freezing Compartment	Noise Level	Picture
I	A	169	120	A++	34	106	15	39	C
	B	239	80	A+++	22	105	14	37	D
II	A	379	180	A+	50	105	13	38	D
	B	449	120	A++	34	104	14	39	C
III	A	259	154	A+	43	104	14	38	A
	B	289	153	A++	43	106	15	39	C
IV	A	239	200	A+	56	106	14	38	A
	B	309	160	A+	45	104	15	37	B
Included in C		✓	✓	✓					
Included in T_C		✓	✓	✓	✓				
Included in T_N		✓	✓	✓		✓	✓	✓	✓

representative rational consumer to be indifferent between alternative A, which is more energy efficient, but also more expensive with respect to the purchase price, and alternative B. Under reasonable assumptions on electricity prices, operating lifetime of the appliance and individual discount rates – i.e. an average electricity price of roughly 29 cent/kWh, 14 years of appliance use, and a discount rate of 14% (24%) –, the median consumer would be indifferent between a 40 kWh (60 kWh) increase in electricity consumption and a price discount of 70 Euro.⁵ Accordingly, we let participants trade off annual energy savings of 40 or 60 kWh against appliance price increases of 70 EUR. Furthermore, in both hypothetical choices, the alternatives differ in the efficiency class, which we determine in accordance with the rules of the EU label throughout all choice sets.

A third choice set aims at identifying the value of efficiency classes per se. Under the provisions of the EU label, higher electricity consumption levels can never lead to better efficiency classes for a given product class. Therefore, orthogonal designs that would independently vary both attributes are unfeasible because they may confuse study participants about the meaning of efficiency classes. To avoid this, we employ knowledge on the assignment mechanism of labels, which requires efficiency classes to be determined based on threshold values for an underlying energy efficiency index (EEI). We calculate such a threshold value for the product class of our choice sets and set electricity consumption closely around it, differing only marginally by 1 kWh so that $\Delta PVO \approx 0$. Fixing the difference in purchase prices at 30 Euro, this setting allows us

⁵Empirical investigations into discount rates yield largely varying results (Frederick et al., 2002), but the range of 14-24% is consistent with many findings and closely matches the discount rates found by Collier and Williams (1999), for example.

to investigate whether a fraction of individuals has a willingness to pay for efficiency classes, independent of electricity consumption.⁶

In choice set IV, we employ the same differences in purchase prices and electricity consumption among alternatives as in choice set I, but choose the level of consumption in a way to avoid differences in efficiency classes, so that $\Delta EC = 0$. Hence, the particular characteristic of choice set IV is that the electricity consumption differs but there is no efficiency class difference so that we can solely focus on the effect of δPVO here.

To test our hypotheses, we use combinations of the choice sets and treatment groups as visualized in Table 2. Choice sets I-II as well as the two information treatments T_S and T_N serve to test the *cost* and *stimuli hypotheses*. Precisely, we test whether the provision of annual electricity cost on the energy label in treatment group T_S increases the probability P_A of choosing the more energy efficient appliance ($\partial P_A / \partial S > 0$) and whether the treatment group T_N , which is shown a label with more attributes that are not related to electricity consumption, opt less frequent for the energy efficient appliance, so that $\partial P_A / \partial N < 0$. Due to its specific design to detect efficiency class valuations, choice set III allows to investigate whether a share of consumers choose the alternative with the higher efficiency class although the energy consumption is almost equal and thus $\Delta PVO \approx 0$. This tests the *heuristics hypothesis*, i.e. $\tau(s, N) > 0$. Furthermore, the combination of the choice sets III and IV with the information treatments T_S and T_N enables us to analyze the *ambiguity hypothesis*. As the hypothesis is formulated in terms of unobservables, such as the attention to operating cost $\theta(S, N)$ and the valuation of efficiency class differences $\tau(S, N)$, it is not directly testable. However, when $\Delta PVO = 0$ (choice set III) or $\Delta EC = 0$ (choice set IV), changes in probabilities to choose alternative A in response to the information treatments are directly linked to changes in $\theta(S, N)$ or $\tau(S, N)$. For example, $\partial P_A / \partial S < 0$ implies $\partial \theta / \partial S < 0$ if $\Delta EC = 0$, as can be seen from Equation (4). Using choice set III and IV, we can therefore infer the effect of the information treatments on both $\tau(S, N)$ and $\theta(S, N)$ by investigating their effect on observable choice probabilities.

⁶Details of the calculation rule are given in EU directive 2010/30/EU. The present value of saving 1 kWh per year corresponds to some 2,9 EUR, assuming a relatively low discount factor of 5%, an electricity price of 29 cent/kWh – which is equivalent to the average residential electricity price in Germany in 2015 (BDEW, 2015) – and a lifetime of 14 years.

Table 2: Overview of Hypotheses

Hypothesis	Choice sets	Core idea of identification strategy
<i>Cost</i>	I and II	Additional cost information on the label solely presented to individuals of treatment group T_C
<i>Stimuli</i>	I and II	Additional attributes on the label solely presented to individuals of treatment group T_N
<i>Heuristic</i>	III	Difference in efficiency classes, when $\Delta PVO \approx 0$
<i>Ambiguity</i>	III and IV	Additional cost information/attributes, when either $\Delta PVO \approx 0$ or $\Delta EC = 0$

4.1. Data

We conducted the discrete choice experiment using the household panel of the German survey institute *forsa*. Each participant was randomly assigned to one of the three groups (C , T_S or T_N) and exposed to all choice sets. To avoid ordering effects (Carlsson et al., 2012; Day et al., 2012), we randomly determined the sequence of both choice sets and the alternatives A and B within choice sets.

Data was collected by *forsa* via a state-of-the-art tool that allows respondents – in our case the household heads – to complete the questionnaire at home. At the outset of the survey questionnaire, we briefly explained the setting and informed households about the meaning of the label attributes and an average lifetime of refrigerators of 14 years in Germany. Participants were requested to assume this lifetime when choosing between appliances (for the detailed text, see Appendix A.1).⁷ The survey took place between March 3 and April 28, 2015, and comprised 5,069 households. In total, 270 of them did not complete it, which corresponds to a dropout rate of 5.3%.⁸ For each survey participant, we observe a large set of socio-economic and demographic background information. The descriptive statistics provided in Table 3 illustrate that covariates are balanced across experimental groups, as expected from the randomization. Furthermore, dropout rates do not differ by treatment status.

The share of women in our sample accounts for some 33%, which reflects our decision to deliberately ask household heads to fill out the questionnaire. About one fifth of our respondents has a college preparatory degree while another fifth holds a college degree. Pro-environmental attitudes, proxied by the statement to be inclined to Germany’s green party are reported for about 9% of the respondents. Net monthly income is measured in intervals of 500 EUR and top-coded at 5,700 EUR. The dummy variable, *uninformed*, equals unity if the consumer indicated to not have any idea about average electricity prices in Germany, which is the case for some 30%

⁷Further information on *forsa* and its household panel is available at www.forsa.com.

⁸These individuals differ significantly in terms of age and gender from the remaining sample as suggested in Table A1 in the Appendix. This table also shows that the remaining sample has similar socio-economic characteristics in comparison with the underlying population of German households.

Table 3: Descriptive Statistics

Variable	Explanation	All	C	T_N	T_S
<i>Age</i>	Age of respondent	55.25	54.87	55.39 (1.31)	55.49 (1.77)
<i>Female</i>	Dummy: 1 if respondent is female	0.333	0.322	0.352 (3.50)	0.325 (0.04)
<i>College Degree</i>	Dummy: 1 if respondent holds a college degree	0.212	0.210	0.217 (0.00)	0.202 (1.03)
<i>Income</i>	Monthly net household income	2,893	2,863	2,898 (0.48)	2,917 (1.14)
<i>Green Attitudes</i>	Dummy: 1 if respondent tends to vote green	0.083	0.074	0.092 (3.40)	0.082 (0.70)
<i>Uninformed</i>	Dummy: 1 if respondent does not know the average electricity price in Germany	0.296	0.297	0.302 (0.11)	0.289 (0.22)
	Share of respondents that did not finalize the survey	0.053	0.056	0.050 (0.14)	0.053 (0.58)

Note: χ^2 -Statistics for mean differences between control group and the treatment groups are in parentheses.

of participants. We conjecture that such individuals have no beliefs about their own electricity prices either.

5. Empirical strategy and estimation results

Heuristic Hypothesis

We start by analyzing whether efficiency classes have a value on its own, i.e. whether $\tau(s, N) > 0$ so that we actually have to consider the full Equation 4. For that purpose we focus on the choice set that is characterized by the existence of differences in purchase prices and energy efficiency classes but only differs marginally in electricity consumption levels (i.e. $\Delta PVO \approx 0$ and $\Delta EC > 0$). This choice set (III) enables us to investigate the extent to which decision heuristics based on efficiency class differences are applied. Specifically, we estimate the following parsimonious linear probability model (LPM):

$$Y_i = \alpha_0 + \epsilon_i, \quad (5)$$

where Y_i is a dummy variable that equals unity when individual i chooses the more energy efficient alternative A and zero otherwise and ϵ_i designates an idiosyncratic error term.⁹

The intercept (*Cons*) in specification (1) in Table 4 illustrates that as many as 66% of the

⁹In order to test for possible effects that may arise from repetitively giving answers to similar choice situations (for instance fatigue effects or ordering effects, e.g. Day et al., 2012), we carried out our analysis considering only respondents' first choices. The results are qualitatively identical to those shown in the following and are available upon request.

Table 4: Test of the *Heuristic Hypothesis*

	(1)		(2)	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Cons	0.656**	(0.012)	0.410**	(0.058)
Female			0.059*	(0.028)
Age			0.004**	(0.001)
Green Attitude			-0.033	(0.048)
High Income			0.012	(0.042)
Uninformed			0.082**	(0.028)
College Degree			-0.056	(0.033)
Number of observations	1,603		1,347	

Note: Standard errors are in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

individuals in the control group are willing to pay at least 30 Euro for an upgrade of the efficiency class, although it is only associated with a marginal reduction of electricity consumption. Taking into account that the present value of a 1 kWh decrease in annual electricity consumption is in the order of magnitude of 3 Euro, this finding strongly supports the *heuristics hypothesis*, indicating that a large share of individuals actually attach value to efficiency classes independent of electricity consumption levels.

We then include various socioeconomic characteristics and personality traits (X_i) in order to analyze heterogeneity in the valuation of efficiency class differences, estimating the following LPM:

$$Y_i = \alpha_0 + \alpha_1' X_i + \epsilon_i. \quad (6)$$

As can be seen from specification (2) in Table 4, reliance on the efficiency class is particularly strong for individuals that are uninformed about the electricity price. Since these individuals exhibit large if not prohibitive search costs for information on operating costs, we argue that the use of efficiency classes as a decision heuristic is particularly plausible in this case. In contrast, individuals with high education levels seem to apply the decision heuristic less often. Under the assumption that this subgroup of individuals has rather low costs of attention (as the cognitive abilities are higher), they are more likely to base their decisions primarily on actual energy consumption differences, without having to resort to decision heuristics. Furthermore, the estimates on the control variables gender and age indicate substantial heterogeneity – women and elderly individuals tend to rely stronger on efficiency classes.

Cost and Stimuli Hypotheses

Next, we analyze the effect of our information treatments. In the context of randomized

Table 5: Causal impact of Treatment Effects

	(I and II)		(III)		(IV)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Cons	0.863**	(0.007)	0.656**	(0.012)	0.714**	(0.011)
T_C	0.029**	(0.010)	-0.042*	(0.017)	0.070**	(0.015)
T_N	-0.022*	(0.011)	0.025	(0.017)	0.000	(0.016)
Number of observations	9641		4804		4717	

Note: Standard errors are in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.

experiments, where treatments are uncorrelated to observable and unobservable characteristics by construction, a simple difference between sample averages is a consistent estimator for the causal effect of treatments (see for example Angrist and Pischke, 2009). Therefore, we test our hypotheses using again a LPM. Specifically, we estimate:

$$Y_i = \alpha_0 + \sum_d \omega'_d T_i^d + \epsilon_i, \quad (7)$$

where T_i^d denotes a treatment group dummy that equals one if individual i is in treatment group $d \in \{C, N\}$ and zero otherwise. Firstly, we investigate choice sets I and II that comprise appliances that differ in purchase price, electricity consumption and label class (i.e. $\Delta PVO > 0$ and $\Delta EC > 0$). The regression results for choice sets I and II reported in Table 5 show that the provision of annual cost information in treatment group T_C fosters the choice of more energy efficient appliances by 2.9 percentage points and we can reject the null hypothesis of no effect. Thus, these results confirm the *cost hypothesis*. In contrast, increasing the number of competing stimuli (T_N) significantly decreases the choice of the more energy efficient appliance by 2.2 percentage points on average which supports the *stimuli hypothesis*.

Ambiguity Hypothesis

The model on choice set III in Table 5 reveals that the effect of providing information on annual cost (T_C) on the choice of the appliance with the higher efficiency class but only marginally lower electricity consumption is negative and statistically significant. This finding illustrates that the inclusion of cost information acts as a substitute for coarser information in form of efficiency classes; a finding that is in line with information search models (e.g. Houde, 2014b). More specifically, we find evidence showing that a part of individuals change the basis for their decision making as soon as more readily available information is provided in the form of electricity cost. The provision of information unrelated to energy efficiency (T_N) turns out to be

insignificant.

Lastly, we focus on choice set IV where the appliances differ in purchase prices and electricity consumption levels but exhibit the same energy efficiency class (i.e. $\Delta PVO > 0$ but $\Delta EC = 0$). This setting allows us to isolate the effect of our information treatments on the attention to operating costs. The model on choice set IV in Table 5 shows that providing annual cost information (T_C) significantly fosters the uptake of the more energy efficient appliance by about seven percentage points when the choice does not reveal differences in efficiency classes. On the other hand, we find that the effect of augmenting the number of competing stimuli, T_N , is not significantly different from zero. Thus, we can partly confirm the *ambiguity hypothesis*: we find that the salience of annual cost information increases the attention to operating cost, while it decreases the valuation of energy efficiency class differences, i.e. $\partial\theta/\partial S > 0$ and $\partial\tau/\partial S < 0$.

In order to investigate for which individuals the treatment effects are particularly strong, we extend our LPM by including both socio-economic characteristics and our treatment effects as well as their interaction terms, yielding:

$$Y_i = \alpha_0 + \alpha'_1 X_i + \sum_d \omega'_d T_i^d + \sum_d \omega'_{d,x} T_i^d X_i + \epsilon_i. \quad (8)$$

Although we estimate fully interacted models for each choice set, Table 6 displays only the coefficients of interest. The fully interacted models can be found in the Appendix A.3. We detect interesting heterogeneous effects in the model for choice set IV, i.e. when differences in efficiency classes are absent. Individuals who live in households with high incomes react to a smaller extent to the provision of annual electricity cost information. This finding is consistent with decreasing marginal utility to income that causes the high-income group to react less strongly to cost information. Further, our results imply that respondents holding a college degree are more likely to opt for the more energy efficient appliance when information, which is unrelated to electricity consumption, is provided ($T_N \# College Degree$). Put differently, respondents without a college degree are guided away from energy efficient choices when the environment is cognitively demanding.

6. Summary and conclusions

This paper investigates the effects of energy label elements on the choice of energy-using durables in the context of the EU energy efficiency label. Using a representative survey with

Table 6: Interaction effects

	(Choice set I and II)		(Choice set III)		(Choice set IV)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Cons	0.821**	(0.038)	0.410**	(0.058)	0.655**	(0.057)
T_C	0.072	(0.050)	-0.232**	(0.083)	0.013	(0.078)
T_N	-0.062	(0.054)	0.107	(0.082)	-0.010	(0.079)
T_C #High Income	-0.025	(0.030)	-0.027	(0.058)	-0.160**	(0.053)
T_N #High Income	0.014	(0.031)	-0.006	(0.058)	-0.071	(0.052)
T_C #College Degree	0.019	(0.026)	0.014	(0.047)	0.068	(0.043)
T_N #College Degree	0.041	(0.028)	0.013	(0.046)	0.135**	(0.043)
Number of observations	8,151		4,063		3,986	

*Note: Only the coefficients of interest of the fully interacted models are displayed. The fully interacted models can be found in the Appendix A.3. Standard errors are in parentheses. **, * denote statistical significance at the 1 % and 5 % level, respectively.*

about 5,000 participants, we conduct a discrete choice experiment to test the role of information treatments and decision heuristics. Building on behavioral insights into the working of inattention, our information treatments vary label elements: we include information on annual electricity cost and increase the complexity of the label by including additional elements that are not related with energy consumption. Last, we investigate to what extent consumers value the label independent from electricity consumption and savings.

We find that providing cost information increases the effectiveness of the EU label to guide consumers to more energy efficient appliances. Specifically, our results indicate that this effect works through increasing attention to operating cost and is especially pronounced when household income is low. Furthermore, our estimates imply that increased complexity of the label lower the purchase rate of energy efficient appliances. Furthermore, our results indicate that it particularly decreases attention to operating cost for individuals with low education levels, which may imply that their costs of attention are especially high. Last, we find that a large share of individuals employ a simplifying decision heuristic by focusing predominantly on efficiency classes, while neglecting the energy consumption attributes. Interestingly, the provision of electricity cost information decreases the share of individuals that rely on efficiency classes, thereby documenting a substitution effect that is consistent with information search models by Houde (2014b) or Sallee (2013), for example.

The results are important as they indicate potential to reduce welfare losses from both internalities as well as from externalities. As energy efficiency labels affecting millions of purchase decisions each year, for instance, alone in the EU-21, about 14.9 million refrigerators were sold in 2014, the developing of an optimal energy efficiency label is of major relevance. Based on our

results that particularly focus on the EU label, we can derive the following policy recommendations. First, we conclude that the effectiveness of the EU label can be improved by adding information on annual electricity costs that could easily be estimated using annual electricity consumption of the appliance as well as average electricity prices in each member state. Second, individuals with low educational background may benefit from a simplification of the label that reduces the cognitive burden of attention to energy efficiency. Accordingly, it may be worthwhile to consider whether information of the noise level as well as the sizes of the cooling and the freezing compartments could be removed from the EU label. Last, the fact that consumers employ decision heuristics may call for adjusting innovation policy. Since producers are not very likely to increase energy efficiency unless their appliances reach a better efficiency class, energy policy has the potential to induce small-scale innovations by lowering thresholds for efficiency classes. While it is an appealing idea to periodically lower the thresholds, the question of its practical applicability calls for further research.

A. Appendix

A.1. Experimental Setting

Please imagine that you are about to purchase a refrigerator (e.g. as in the illustration). For your information: The average lifespan of a refrigerator in Germany is about 14 years.

In the following, we would like to ask you to compare two refrigerators. The appliances are presented on the basis of the EU label and they differ in the following features: [images including explanation of each label element shown]

Successively, we will show you four pairs of refrigerators. Please assume that all features not mentioned are completely identical (number of compartments, brand, etc.). Please select in each case the appliance, you would purchase if you had to choose one of the two. Which of the following alternatives would you choose?

A.2. Descriptive Statistics

Table A1: Comparison of Remaining Sample with Dropouts, and the Underlying Population

Variable	Remaining Sample	Dropouts	χ^2	Population
<i>Age</i>	55.13	56.19	(3.38*)	53.28
<i>Female</i>	0.330	0.442	(26.73***)	0.353
<i>Low Education</i>	0.580	–		0.665
<i>Medium Education</i>	0.210	–		0.138
<i>High Education</i>	0.210	–		0.197
<i>Low Income</i>	0.203	–		0.389
<i>Medium Income</i>	0.679	–		0.501
<i>High Income</i>	0.118	–		0.110
<i>Green</i>	0.197	–		n.a.
<i>Not Informed</i>	0.285	–		n.a.

Note: χ^2 -Test values for differences between the remaining sample and dropouts and skippers, respectively in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level, respectively. Data for the population is drawn from Destatis (2014). Yet, it is not unconditionally comparable. For instance, Destatis (2014) asks the main earner to complete the questionnaire instead of the household member that normally makes decisions on the household level as in our case. Further, age is expressed in categories of ten years. To compute the average we assume that individuals are equally distributed within each category. Further, household monthly net income is given in categories that differ from those we used in our survey.



(a) Refrigerator A



(b) Refrigerator B



(c) Refrigerator C



(d) Refrigerator D

Figure A1: Pictures of Refrigerators

A.3. Fully Interacted Models

Table A2: Causal Impacts

	(Choice set I and II)		(Choice set III)		(Choice set IV)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Cons	0.821**	(0.038)	0.410**	(0.058)	0.655**	(0.057)
T_C	0.072	(0.050)	-0.232**	(0.083)	0.013	(0.078)
T_N	-0.062	(0.054)	0.107	(0.082)	-0.010	(0.079)
Female	0.031	(0.016)	0.059*	(0.028)	0.035	(0.027)
Age	0.001	(0.001)	0.004**	(0.001)	0.001	(0.001)
Green Attitude	0.056*	(0.025)	-0.033	(0.048)	0.053	(0.044)
High Income	0.035	(0.023)	0.012	(0.042)	0.107**	(0.038)
Uninformed	-0.030	(0.018)	0.082**	(0.028)	-0.041	(0.029)
College Degree	-0.018	(0.019)	-0.056	(0.033)	-0.059	(0.032)
T_C #Female	-0.026	(0.022)	0.043	(0.039)	-0.041	(0.037)
T_N #Female	0.012	(0.024)	0.042	(0.038)	-0.010	(0.038)
T_C #Age	-0.001	(0.001)	0.003*	(0.001)	0.002	(0.001)
T_N #Age	0.001	(0.001)	-0.002	(0.001)	0.000	(0.001)
T_C #Green Attitude	-0.013	(0.032)	0.092	(0.066)	0.055	(0.055)
T_N #Green Attitude	-0.024	(0.035)	0.073	(0.064)	-0.032	(0.059)
T_C #High Income	-0.025	(0.030)	-0.027	(0.058)	-0.160**	(0.053)
T_N #High Income	0.014	(0.031)	-0.006	(0.058)	-0.071	(0.052)
T_C #Uninformed	-0.009	(0.025)	-0.013	(0.041)	-0.039	(0.040)
T_N #Uninformed	-0.023	(0.027)	-0.078	(0.040)	-0.010	(0.041)
T_C #College Degree	0.019	(0.026)	0.014	(0.047)	0.068	(0.043)
T_N #College Degree	0.041	(0.028)	0.013	(0.046)	0.135**	(0.043)
Choice Set Fixed Effects	Yes		No		No	
N	8,151		4,063		3,986	

Note: Standard errors are in parentheses and clustered at the individual level. **, * denote statistical significance at the 1 % and 5 % level, respectively.

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