Energy Economics 84 (2019) 104527

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Cognitive reflection and the valuation of energy efficiency☆

Mark A. Andor[a], Manuel Frondel[b], Andreas Gerster[c,*], Stephan Sommer[a]

[a] RWI – Leibniz Institute for Economic Research, Germany
[b] RWI – Leibniz Institute for Economic Research and Ruhr University Bochum, Germany
[c] University of Mannheim, L7, 3-5, 68161 Mannheim, Germany

ARTICLE INFO

Article history:
Received 21 January 2019
Received in revised form 1 July 2019
Accepted 2 October 2019
Available online 17 October 2019

JEL classification:
D03
D12
D83
Q48
Q50

Keywords:
Environmental certification
Decision heuristics
Energy-using durables

ABSTRACT

Based on a stated-choice experiment among about 3600 German household heads on the purchase of electricity-using durables, this paper explores the impact of cognitive reflection on consumers' valuation of energy efficiency, as well as its interaction with consumers' response to the EU energy label. Using a standard cognitive reflection test, our results indicate that consumers with low cognitive reflection value energy efficiency less than those with high scores. Furthermore, we find that consumers with a low level of cognitive reflection respond strongly to grade-like energy efficiency classes and tend to disregard detailed information on annual energy use, while the opposite holds true for consumers with a high level of cognitive reflection.

1. Introduction

Consumers' hesitation to invest in cost-effective energy efficiency technologies, commonly referred to as the "energy efficiency gap" (Jaffe and Stavins, 1994), has been a puzzle in energy and environmental economics for decades. A plethora of factors have been proposed to explain the gap (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014), including classic market failures due to information asymmetries, bounded rationality of consumers, as well as inattention to energy efficiency (Allcott and Taubinsky, 2015). Partly, this inattention can be explained by the presence of cognitive-effort cost when evaluating product attributes for the purchase decision on energy-using durables (see e.g. Gabaix, 2014).

Consumers frequently aim at minimizing such costs by employing decision heuristics, provided for instance by energy labels, and also tend to pay less attention to opaque lifetime energy cost than to salient purchasing prices (Allcott and Taubinsky, 2015).

Energy labels, such as those employed in the European Union, present coarse summary information on energy consumption by categorizing appliances into grade-like efficiency classes. Providing such information facilitates the evaluation of product attributes with minimal cognitive effort. Against this background, cognitive reflection, describing a person's ability to resist reporting an intuitive response prior to having second thoughts about its correctness, can be assumed to be an important explanatory factor for consumers' valuation of energy efficiency.

Based on data orgininating from a sample of around 3600 German household heads and the cognitive reflection test suggested by Frederick (2005), this paper investigates this assumption by estimating the impact of cognitive reflection on consumers' valuation of energy efficiency. Given that cognitive reflection is considered to be an important measure of cognitive abilities in the literature (Frederick, 2005), we also analyze whether it moderates individuals' response to two defining elements of the European Union (EU) energy label: energy efficiency classes and annual electricity usages. Methodologically, we couple stated-choice experiments on the purchase of refrigerators with randomized information treatments. Stated-choice experiments ask participants to choose among a set of alternatives that differ in at least one attribute, thereby allowing to infer preference parameters, such as the individual willingness-to-pay for energy efficiency (Carson and Louviere, 2011; McFadden, 2017). Our information treatments vary whether energy efficiency classes are displayed in addition to basic information about annual electricity usages of refrigerators. Cou-

☆ Publication of this supplement was supported by ETH Zürich, the University of Münster and Economics for Energy.

* Corresponding author.
E-mail address: gerster@uni-mannheim.de (A. Gerster).

https://doi.org/10.1016/j.eneco.2019.104527
0140-9883/

pled with an elicitation of cognitive reflection as suggested by Frederick (2005), this approach allows us to assess the role of individuals' cognitive reflection for their perception of these defining elements of the EU label.

In our experiment, participants are randomly assigned to two groups: in the first group, based on information as given by the EU energy label, participants make three binary choices on two refrigerators with varying energy efficiencies. By contrast, participants of the second group make their decisions on the basis of modified EU label information, where efficiency classes are omitted. All choice sets include a benchmark refrigerator, which allows us to trace out the demand curve over the range of electricity consumption values relative to this benchmark.

Our focus on cognitive reflection is inspired by a large literature that has demonstrated this factor's strong influence on decision-making in many settings. Frederick (2005) and Dohmen et al. (2010), for instance, show that cognitive reflection, as measured by cognitive reflection test (CRT) scores, is significantly related to both time- and risk preferences. Oechssler et al. (2009), as well as Hoppe and Kusterer (2011) find that individuals with low CRT scores are more likely to be affected by behavioral biases, such as anchoring and overconfidence. In their analysis on the effects of free-riding on a rebate program for heating systems, Olsthoorn et al. (2017) include cognitive reflection as a control variable, finding that respondents with a higher level of cognitive reflection demand higher rebates and are less prone to be free riders.

Our work builds on this research by being the first to investigate the relationship among cognitive reflection, valuation of energy efficiency, and the response to information from energy labels. The literature on energy labels has instead focused on the impact of alternative label designs on the valuation of energy efficiency and the uptake of efficient appliances (for an overview see Andor and Fels, 2018). For example, Hille et al. (2018) and Waechter et al. (2015) show that efficiency classes can induce consumers to falsely perceive energy-intensive products as environmentally friendly. Moreover, Andor et al. (2017) and Houde (2018) find that consumers have a positive willingness-to-pay for products with a high efficiency ranking, which can even exceed the economic value of the underlying energy use differences. Other studies have analyzed the implications of adding operating cost information to energy labels, yielding mixed results (Andor et al., 2017; Newell and Siikamäki, 2014; Stadelmann and Schubert, 2018). Using revealed rather than stated preferences, Andor et al. (2019) demonstrate that providing lifetime energy cost substantially increases the willingness-to-pay (WTP) for energy-efficient light bulbs, while the current EU label has no effect on the WTP.

Few studies have investigated the mechanisms through which energy labels affect decision-making. One rare example is Blasch et al. (2019), who find that presenting operating cost information helps consumers in identifying the appliance with lowest lifetime cost. More broadly, Brounen et al. (2013) show that only about half of the consumers are "energy literate" in the sense that they know their monthly energy charges and appropriately evaluate their energy efficiency investments.

By focusing on the role of cognitive reflection, we go beyond the contributions of Blasch et al. (2019) and Brounen et al. (2013) and present numerous novel empirical outcomes. First, our results demonstrate that consumers with higher cognitive reflection scores value energy efficiency more than those with lower scores. Second, we find that consumers with low cognitive reflection respond most strongly to the presentation of efficiency classes. Furthermore, we replicate the "class valuation effect", according to which consumers have a willingness-to-pay for a better efficiency class *per se*, i.e. irrespective of the underlying energy use differences, as well as the "information substitution effect" documented in previous research (Andor et al., 2017; Houde, 2018). This notion

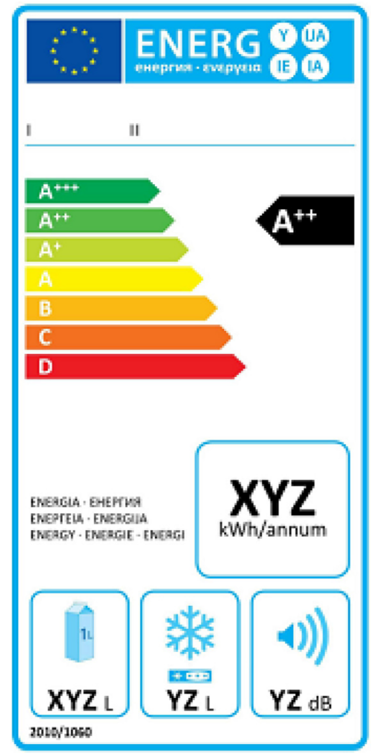


Fig. 1. EU energy label for refrigerators.

describes the effect by which the provision of efficiency class information crowds out the valuation of more detailed information on energy consumption. Third, we find that both effects are particularly pronounced among respondents with low levels of cognitive reflection, suggesting that the mechanism through which efficiency classes affect choices is the reduction of cognitive effort.

Our stated-preference study adds to numerous hypothetical analyses that investigate the impact of alternative label schemes (see e.g. Newell and Siikamäki, 2014 and Andor et al., 2017). Employing a stated-preference approach has several advantages; first, it allows collecting a rich set of individual-level characteristics, including measures of cognitive reflection, which are highly informative about the mechanisms of decision-making, but typically unavailable in field studies. Second, by varying information provision in a controlled environment, for instance by removing the efficiency class from the EU label, our approach allows for a tailored research design that would be infeasible in real-world settings.

The subsequent Section 2 describes the EU energy label for refrigerators. In Section 3, we describe our experimental design and the data. Section 4 presents our empirical results, while Section 5 discusses our findings and concludes.

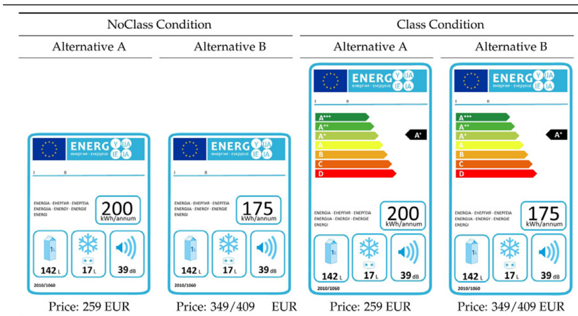
2. The EU label for refrigerators

Our analysis focuses on refrigerators, as their penetration rate reaches nearly 100% in almost all EU member states (Bertoldi et al., 2012) and their electricity use is largely independent of consumers' behavior. Whenever household appliances are offered for sale in the EU, the energy label must be displayed on the appliance. As visualized in Fig. 1, the label for refrigerators depicts the annual electricity consumption and an energy efficiency class ranging from D (least efficient) to A+++ (most efficient). The label also presents information on the capacity of fresh food and frozen food compartments, as well as the noise level. Since July 2012, due to the imposition of minimum standards (EU Directive 2009/125/EC), refrigerators that do not reach class A+ are banned from the EU market.

Table 1
Binary choice sets.

Choice sets	1–12	1/7	2/8	3/9	4/10	5/11	6/12
Alternative	A	B	B	B	B	B	B
Available on the market	x			x		x	
Efficiency class	A+	A+	A+	A++	A++	A+++	A+++
Electricity use in kWh	200	175	151	150	101	100	85
Price in EUR	259	349/409	349/409	349/409	349/409	349/409	349/409

Table 2
Illustration of the choice alternatives.



To assign efficiency classes to refrigerators, the EU legislation prescribes the calculation of an energy efficiency index (EEI), which is a function of the electricity use of the appliance, its product class, and its size (details on the calculation rules are given in EU Directive 2010/30/EU). By construction, lower EEI values are associated with higher energy efficiency. The efficiency class of an appliance results from whether its EEI falls below predefined cutoff values.

3. Experimental design and data

At the beginning of the experiment, we informed all participants about the meaning of the label attributes (details are given in Appendix A.1). For our binary-choice experiment, we created 12 binary choice sets.[1] Each of them comprised the choice between two refrigerators that differ in their purchasing price, efficiency class, and electricity consumption (see Table 1). Taking market prices and refrigerator characteristics from the online portal of a large German retailer for consumer electronics, we let participants trade off annual electricity savings between 25 and 115 kWh against higher purchasing prices of either 90 or 150 EUR (Table 2). To avoid confounding effects from attributes other than purchasing price, efficiency class, and electricity consumption, we kept information on size, volume, and noise of the refrigerator constant across choice sets.

All choice sets included a benchmark refrigerator with an annual electricity consumption of 200 kWh (Alternative A). Varying the product attributes of Alternative B over the 12 choice sets allows us to trace out the demand curve over a range of electricity consumption values relative to Alternative A. For expositional purposes, in the manuscript, the more energy-efficient appliance is denoted as Alternative B throughout, whereas in the experiment, the more energy-efficient appliance was randomly presented as either Alternative A or B.[2]

To identify consumers' response to differences in both electricity use and efficiency classes, we deliberately conceived a number of hypothetical appliances, but some of our choice sets also included appliances that were actually offered at the market. Our approach to primarily present hypothetical appliances is due to the fact that producers strategically respond to the EU label in that they do not vary the energy efficiency of appliances continuously, but in increments to reach a better efficiency class (see e.g. Houde, 2014 and Andor et al., 2017). To avoid choice fatigue (see, for instance, Augenblick and Nicholson, 2015), we presented only three randomly selected choice sets out of the 12 available sets conceived to each participant. In this respect, it bears noting that our point estimates remain largely unchanged when only the first choice of each respondent is used for the estimations (see Table A.3 in the appendix).

We randomly assigned households to one of two experimental groups (see Table 2). In the first group, here referred to as Class Condition, participants chose between two refrigerators on the basis of information that is given by the EU energy label. In the second group, here called NoClass Condition, participants received information on the appliances based on a modified version of the EU label in which efficiency classes were omitted.

In addition to the binary-choice experiment, based on multiple price lists, participants were confronted with a choice situation with which we elicited their individual willingness-to-pay (WTP) for both energy efficiency and efficiency classes. To this end, we randomly presented participants either of two kinds of binary-choice sets, denoted by Multiple Price List I and II (Table 3), thereby maintaining the experimental condition from the binary choice experiment. Thus, respondents in the NoClass Condition would not see efficiency class information in the experiment involving multiple price lists. For either list, participants were requested to choose between the more energy-efficient appliance B and the less efficient appliance A at eight purchasing price differences, ranging from −20 to 120 EUR (see Table A.1 in the appendix for a detailed overview).

Multiple Price List I serves to identify the valuation of efficiency classes *per se*. Following Andor et al. (2017), we set the annual electricity usage of the two Alternatives A and B at 150 and 151 kWh, with 150 kWh corresponding to the class cutoff value between the efficiency classes A+ and A++. Hence, by design, A and B's electricity consumption rates differ only marginally, by 1 kWh, but both alternatives belong to different efficiency classes. Multiple Price List II serves to elicit the WTP for given electricity savings and efficiency classes. In detail, we ask participants to choose between two appliances belonging to the same efficiency class, but differing in annual electricity usage by 49 kWh. This figure equals the maximum difference in electricity consumption of appliances within the same efficiency class.

[1] The choice sets are based on product data provided on the website of Media Markt. Comparing appliances of a given brand, the median difference in electricity consumption rates amounts to 55 kWh per year, with an interquartile range from 19 to 98 kWh. The median difference in purchasing prices amounts to EUR 90, with an interquartile range from EUR 40 to EUR 200.

[2] With our research design, we do not aim at maximizing statistical efficiency, for example by employing orthogonal designs. Rather, following (Johnson et al., 2013), our aim is to provide unbiased estimates of participants' valuation of energy use and efficiency class differences. To achieve sufficient statistical power, we rely on a large sample. Note that energy efficiency classes are a deterministic function of annual energy consumptions, so that orthogonal designs are infeasible as they would confuse individuals about the meaning of such classes.

Table 3
Choice sets used for multiple price lists.

Attributes	Mutiple price list I		Multiple price list II	
	Alternative A	Alternative B	Alternative A	Alternative B
Efficiency class	A+	A++	A++	A++
Electricity use in kWh	151	150	150	101
Price in EUR	319	299–439 (in steps of 20 EUR)	319	299–439 (in steps of 20 EUR)

The experiment was embedded in a survey that was conducted by the survey institute *forsa* using its household panel.[3] Data was collected in 2017 between June 7 and July 23, via a survey tool that allows participants to complete the questionnaire via the internet or by television. Respondents, in this case household heads, could interrupt and continue the survey at any time. Household heads are defined as those individuals who are responsible for financial decisions at the household level, such as the purchase of a refrigerator.

In total, 3608 household heads were randomly assigned to either the Class or the NoClass Condition. 59 respondents quit the survey prior to or during the experiment and hence were not taken into account in the subsequent analysis. Around 43% of the respondents are female and about one quarter graduated from college. Pro-environmental attitudes were measured by a variant of the Diekmann-Preisendörfer (Diekmann and Preisendörfer, 1998) scale, which we normalized to unity.[4] As becomes evident from Table A.2, most socio-economic characteristics of our sample closely match the characteristics of the population of German household heads.

To measure cognitive reflection, we employed the three-item "Cognitive Reflection Test" (CRT) suggested by Frederick (2005). This test consists of three simple math problems for which intuitive – yet incorrect – solutions suggest themselves (for details, see Appendix A.2). Slightly more than a third of the respondents did not provide a correct answer to any of the three questions, whereas only 18.2% answered all of them correctly (Table 4). Following Frederick (2005), we classified cognititve reflection "low" if a respondent answered no question correctly (CRT = 0) and as "high" if a respondent provided three correct answers (CRT = 3). Those respondents who answered either one or two questions correctly were assigend to a third group, characterized by CRT = 1 or 2.

4. Model specifications and empirical results

As a result of randomization in the assignment of information treatments, the means of the covariates are very similar across experimental groups (Table 4). Using *t* tests for mean differences, we cannot reject the null hypothesis of no difference across groups at the 5% significance level throughout. By contrast, the percentage of participants choosing the more energy-efficient refrigerator differs across experimental groups. Most notably, in the experimental group in which efficiency classes are presented to the respondents (Class Condition), the share of those who chose the more energy-efficient appliance B is 1.7 percentage points higher than in the NoClass Condition, where the respective share equals 75.4% (Table 4). This difference is statistically significant at the 5% level.

It bears noting that this difference more than triples and increases to 6.2 percentage points, when we focus on choices between refrigerators that are offered at the German market. Moreover, those participants who confronted with the choice between Alternative A and B chose the option "I do not know" are excluded from the analysis. As these comprise only 3.5% of the respondents and the percentages are statistically indistinguishable across the experimenal conditions, their exclusion does not bear on our results.

4.1. Binary choice experiment

Starting with the presentation of the results obtained from the binary-choice experiment, we first explore the impact of cognitive reflection on participants' choices using the following linear probability model for the NoClass Condition:[5]

$$B_{ij} = \beta + \beta_{12}(\text{CRT} = 1 \quad \text{or} \quad 2)_i + \beta_3(\text{CRT} = 3)_i + \beta_U \Delta U_j + \beta_P(\Delta P = 150)_j + \epsilon_{ij}, \tag{1}$$

where B_{ij} is a dummy variable that equals unity if individual i chooses the more energy-efficient Alternative B in choice set j and equals zero otherwise, and ϵ denotes the error term. CRT = 1 or 2 and CRT = 3 denote dummy variables that reflect the results of the cognitive reflection test scores of individual i, with the first variable equalling unity if i provided either one or two correct answers and the second variable equalling unity if i provided three correct answers. Those individuals who answered all three questions incorrectly are the reference respondents. ΔU_j denotes the difference in electricity usage between Alternative B and A in choice set j and $\Delta P_j = 150$ is a binary indicator for whether the appliance shown in Alternative B is EUR 150 more expensive than that of Alternative A, rather than just EUR 90.

The linear probability model for the Class Condition additionally incorporates a dummy variable ΔEC that equals unity if Alternative B in choice set j qualifies for a higher efficiency class:

$$B_{ij} = \beta + \beta_{12}(\text{CRT} = 1 \quad \text{or} \quad 2)_i + \beta_3(CRT = 3)_i + \beta_U \Delta U_j + \beta_P(\Delta P = 150)_j + \beta_{EC} \Delta EC_j + \epsilon_{ij}. \tag{2}$$

To account for serial correlation of the error terms in subsequent choices of a participant, we cluster standard errors at the individual level when estimating these linear probability models.

As can be seen from the results of linear probability model (1), which are reported in Table 5, participants tend to choose the energy-efficient appliance more often as the associated energy savings ΔU increase. Moreover, participants clearly respond to appliance prices, i.e. the demand for the more energy-efficient appliance is lower when the price mark-up relative to Alternative A amounts to ΔP = EUR 150, rather than just EUR 90.[6]

[3] Information on the panel is available at http://www.forsa.com/.

[4] We use four of the nine original questions proposed by Diekmann and Preisendörfer (1998), covering all three spheres of the scale – affective, cognitive, and conative. Our shorter version of the scale yields a Cronbach's (1951) Alpha of α = 0.762, which is very similar to the mean Alpha for measuring attitudes in Peterson's (1994) meta analysis.

[5] We prefer linear probability models in our analysis, as the coefficients can be interpreted as marginal effects and the interaction terms are, in contrast to nonlinear models, easy to interpret. As a robustness check, we estimated a probit model, whose results, reported in Table A.7 of the appendix, are very similar to those of the linear probability model.

[6] The findings presented in Table 5 resemble the results of a fully interacted model in which $Class_i$, a binary indicator that equals unity if respondent i is assigned to the

Table 4
Summary statistics.

	All	Class	NoClass	NoClass-Class	*t* Statistics
Covariates					
Female	0.422	0.413	0.431	0.018	1.043
Age	54.0	53.7	54.2	0.480	0.888
Household size	2.116	2.138	2.093	−0.045	−1.406
Children	0.152	0.163	0.142	−0.020	−1.649*
Homeowner	0.541	0.554	0.528	−0.026	−1.571
College degree	0.258	0.256	0.260	0.004	0.285
Household net income	2773	2813	2733	−79.0	−1.631
Pro-environmental attitudes	0.747	0.743	0.751	0.008	1.375
CRT score = 0	0.346	0.342	0.351	0.009	0.522
CRT score = 1 or 2	0.471	0.483	0.459	−0.024	−1.364
CRT score = 3	0.182	0.175	0.190	0.015	1.120
Outcomes					
Choice of Alternative B	0.762	0.771	0.754	0.017	2.09**
Choice of Alternative B (market choices)	0.791	0.822	0.760	0.063	4.51***
WTP for class differences	32.3	41.8	22.7	19.2	8.91***
WTP for usage differences	81.4	78.6	84.1	−5.4	−2.43**
No. of respondents	3549	1772	1777	–	–

Note: ***, **, and * denote statistical significance at the 1%, 5% level and 10% level, respectively, between sample means across the two experimental groups.

Table 5
Choice of the more energy-efficient appliance B in the binary choice experiment.

	NoClass Condition				Class Condition			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
CRT = 1 or 2	−0.014	(0.018)	−0.179***	(0.041)	−0.008	(0.017)	−0.124***	(0.039)
CRT = 3	−0.011	(0.022)	−0.254***	(0.051)	0.003	(0.021)	−0.109**	(0.049)
Δ U	0.400***	(0.019)	0.229***	(0.032)	0.280***	(0.026)	0.187***	(0.045)
CRT = 1 or 2 × Δ U	–	–	0.226***	(0.043)	–	–	0.144**	(0.058)
CRT = 3 × Δ U	–	–	0.337***	(0.053)	–	–	0.128*	(0.076)
Δ EC	–	–	–	–	0.109***	(0.019)	0.095***	(0.032)
CRT = 1 or 2 × Δ EC	–	–	–	–	–	–	0.016	(0.042)
CRT = 3 × Δ EC	–	–	–	–	–	–	0.029	(0.055)
Δ*P* = 150	−0.149***	(0.012)	−0.151***	(0.012)	−0.136***	(0.011)	−0.136***	(0.011)
Constant	0.548***	(0.021)	0.673***	(0.030)	0.565***	(0.021)	0.642***	(0.030)
Equivalent price metrics								
Δ U	4.026***	(0.370)	2.280***	(0.366)	3.080***	(0.375)	2.065***	(0.524)
CRT = 1 or 2 × Δ U	–	–	2.250***	(0.462)	–	–	1.597**	(0.658)
CRT = 3 × Δ U	–	–	3.354***	(0.590)	–	–	1.411*	(0.851)
Δ EC	–	–	–	–	119.914***	(23.352)	105.489***	(36.539)
CRT = 1 or 2 × Δ EC	–	–	–	–	–	–	17.363	(46.714)
CRT = 3 × Δ EC	–	–	–	–	–	–	31.980	(61.142)
No. of observations	4701		4701		4782		4782	
No. of respondents	1590		1590		1612		1612	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5% level and 10% level, respectively. We have dropped all respondents who chose the option "I don't know" in all three choice sets ($n = 72$) and, in addition, those who did not answer the CRT completely ($n = 275$).

To translate effect sizes into monetary terms, we calculate the equivalent price metrics by dividing each coefficient estimate by the estimate of $\beta_P/150$, while standard errors are approximated using the Delta Method. The results, presented at the bottom panel of Table 5, indicate that respondents value a permanently lower electricity consumption of 1 kWh by about EUR 4.03. This amount is slightly below its undiscounted lifetime value of about EUR 4.1, assuming a lifetime of 14 years and an average electricity price of EUR 0.29 per kWh. Accordingly, we do not find evidence that – on aggregate – consumers undervalue energy efficiency, which supports the findings by Newell and Siikamäki (2014).[7]

As in the NoClassCondition, respondents who face the Class Condition are more likely to opt for the energy-efficient appliance as electricity savings ΔU increase (see Specification 3 of Table 5). Yet, when efficiency classes are shown in the Class condition, the demand curve responds in two ways. First, the large positive estimate for ΔEC, which is statistically significant at any conventional level, leads us to the conclusion that displaying the efficiency classes creates jumps in the adoption of more energy-efficient appliances at the efficiency class cutoff, even when the energy savings are marginal, an effect that we henceforth denote *class valuation effect* (Andor et al., 2017).[8]

Class Condition and zero otherwise, is interacted with ΔU and ΔEC (see Table A.4 of the appendix.

[7] When assuming a 5% discount rate, as in Newell and Siikamäki (2014), the discounted lifetime value of a 1 kWh decrease in electricity use over 14 years is EUR 2.1. Given that the equivalent price metrics for ΔU amounts to 4.0 (Column 1 of Table 5) and 3.1 (Column 3 of Table 5), our results indicate that respondents even tend to overvalue energy efficiency.

[8] Given our experimental design, there are two jumps in the adoption of more efficient appliances, namely at those cutoff values that discriminate between A+++ to A++ as well as A++ to A+, respectively. While the estimates reported in the main text account for the difference in both jumps, Table A.5 in the appendix presents the results of a model where we split the class jumps, but the findings are similar to the estimates in Table 5.

Second, the coefficient estimate on ΔU is significantly lower compared to the NoClass Condition ($\chi^2 = 13.94$, $p < 0.000$), suggesting that if efficiency classes are displayed, the demand curve for more efficient appliances becomes flatter between efficiency class thresholds. This flattening of the demand curve indicates that displaying efficiency classes prompts some participants to neglect the detailed information on the electricity consumption of an appliance and to lower their valuation of electricity savings, which reflects the *information substitution effect* (Andor et al., 2017; Houde, 2018).

Next, we examine whether cognitive reflection affects both the valuation of electricity savings and efficiency classes. For starters, to examine heterogeneity in the valuation of energy efficiency, we include interaction terms in which CRT scores are multiplied by ΔU, finding substantial differences across respondents with different degrees of cognitive reflection. Most notably, respondents with higher CRT scores value differences in electricity consumption more than those with low scores: In the NoClassCondition, for instance, the WTP for a permanent electricity saving of 1 kWh amounts to EUR 2.28 for respondents with the lowest CRT scores, but rises to EUR 2.28 + 2.25 = EUR 4.53 and EUR 2.28 + 3.35 = EUR 5.63 for respondents with higher cognitive reflection (see Specification 2 of Table 5). We find very similar results for the Class Condition (see Specification 4 in Table 5), albeit the effect sizes are somewhat smaller.

Although the coefficient estimates of the interaction terms (CRT = 1 or 2) $\times \Delta$EC and (CRT = 3) $\times \Delta$EC are positive, they are not significantly different from zero in statistical terms, leaving us with uncertainty about the magnitude of the interaction effect of cognitive reflection with efficiency classes. This result changes, however, when using multiple price lists, an approach that is pursued in the subsequent section. This approach has at least two advantages. First, it provides us with rich individual-level data on the relative WTP for the more energy-efficient appliance, rather than just a binary indication of the preference of one alternative over another, thereby affording high statistical power in detecting treatment effects. Second, employing analternative elicitation method allows for testing the robustness of our results.[9]

4.2. Multiple price lists

To analyze the interplay of the *class valuation* and *information substitution* effects and cognitive reflection, we elicit individuals' WTP for electricity savings based on an experiment that uses multiple price lists and estimate the following OLS model:

$$\begin{aligned} WTP_i = \; & \beta + \beta_c Class_i + \beta_{12}(\text{CRT} = 1 \text{ or } 2)_i + \beta_3(\text{CRT} = 3)_i \\ & + \beta_{c12} Class_i \cdot (\text{CRT} = 1 \text{ or } 2)_i + \beta_{c3} Class_i \cdot (\text{CRT} = 3)_i + \epsilon_i, \end{aligned} \quad (3)$$

where the experimental group indicator $Class_i$ equals unity if efficiency class information is presented to respondent i and zero otherwise and the dependent variable WTP_i is computed as the price difference between those two appliances for which respondent i switches from the more energy-efficient Alternative B to the efficient Alternative A. For instance, when a respondent prefers Alternative B at a price difference of EUR 40, yet Alternative A at a price difference of EUR 60, we set the WTP to EUR 50. If Alternative B is chosen over the entire price range, we set the WTP to EUR 120 and if Alternative A is chosen over the entire price range to −20. To investigate whether presenting efficiency classes has varying effects across respondents with different CRT scores, we include the interaction terms $Class \cdot (\text{CRT} = 1 \text{ or } 2)$ and $Class \cdot (CRT = 3)$.[10]

We excluded all those participants who provided incomplete information to compute the WTP (n = 883 cases) and who on top did not answer the CRT completely (n = 190 cases) or behaved inconsistently, that is, switched multiple times between the two alternatives (n = 107 cases). In the end, 2369 observations have been used for the analysis, the results of which are reported in Table 6.[11]

According to the results obtained for Specification 1 of Table 6, displaying the efficiency class increases the WTP by, on average, EUR 18.7 even when the underlying reduction in electricity consumption just amounts to 1 kWh (see Table 4). This outcome reflects the *class valuation effect* that already emerges from the binary choice experiment.

Furthermore, our results indicate that the class valuation effect is moderated by cognitive reflection: respondents with high CRT scores correctly value the small electricity saving of 1 kWh much less than respondents with low scores. In fact, the negative coefficient estimate pertaining to the interaction term $Class \cdot (CRT = 3)$ suggests that respondents with the highest CRT score increase their WTP substantially less when efficiency classes are displayed than respondents with low scores (see Specification 2 of Table 6). The coefficient of the interaction term $Class \cdot (\text{CRT} = 3)$ is statistically significant at the 5% level. Reflecting the higher degree of statistical power when using the multiple price lists, this analysis allows us to provide more precise estimates on the interaction effect between efficiency classes and the cognitive reflection compared to the binary choice experiment, where we could not reject the null hypothesis of zero interaction effects. In short, our results demonstrate that individuals with high cognitive reflection are substantially less likely to base their decision-making on efficiency classes and are thus less prone to the *class valuation effect* than individuals with low CRT scores.

Turning now to the results for Multiple Price List II, we identify the valuation of electricity savings by analyzing a purchase decision where the annual electricity consumption of the two refrigerators of the choice set differs by 49 kWh. This amount corresponds to the maximum difference that is possible for appliances within the same efficiency class. We find that respondents with a higher cognitive reflection tend to have a notably higher WTP than those with lower scores (Specification 3 of Table 6). For instance, individuals with the maximum CRT score have a WTP for the energy-efficient refrigerator that is almost EUR 14 higher than the WTP of individuals with a zero CRT score.

Finally, our results from the Multiple Price List II confirm the *information substitution effect* that we found using the binary-choice experiment. Specifically, participants in the Class Condition value the energy use difference of 49 kWh by about EUR 6.4 less on average (Specification 3 of Table 6). Furthermore, the positive coefficients on the interaction terms $Class \cdot (\text{CRT} = 1 \text{ or } 2)$ and $Class \cdot (\text{CRT} = 3)$ suggest that respondents with higher cognitive reflection do not adjust their valuation for electricity savings as strongly as respondents with CRT = 0 when efficiency classes are displayed (Specification 4 of Table 6). Fig. 2 illustrates these findings by plotting the mean WTP across CRT scores, indicating that presenting efficiency classes primarily influences the decision-making of individuals with low cognitive reflection scores. Individuals with a higher level of cognitive reflection are also influenced by the pre-

[9] The corresponding confidence intervals range from −0.067 to 0.098 and from −0.079 to 0.137 percentage points,respectively, so that we cannot exclude meaningful positive and negative effect sizes.

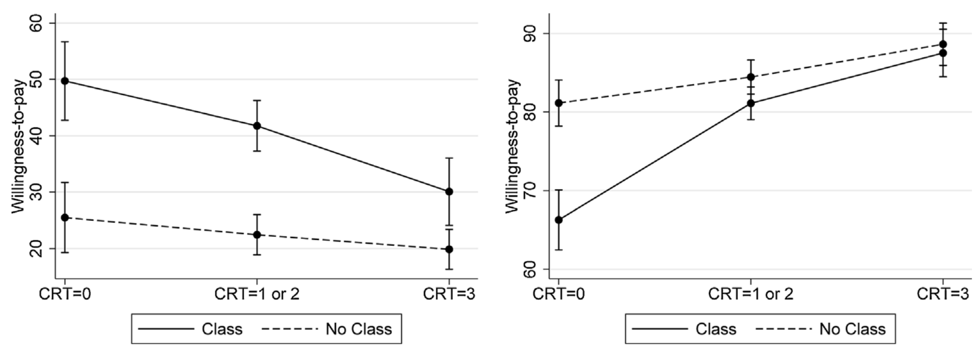
[10] Note that the results are qualitatively the same when we controll for socioeconomic characteristics (see Table A.6 in the appendix.

[11] As a robustness check, we also estimated a Tobit model where the dependent variable is censored at zero. The results, reported in Table A.8, are very similar to those resulting from the linear probability model that we discuss in the main text.

Table 6
Willingness-to-pay for differences in the efficiency class and electricity usage.

	Multiple price list I (ΔU = 1 kWh, ΔEC = 1)				Multiple price list II (ΔU = 49 kWh, ΔEC = 0)			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
CRT = 1 or 2	−5.664**	(2.813)	−3.054	(3.652)	8.417***	(2.799)	3.308	(3.639)
CRT = 3	−12.443***	(2.958)	−5.634	(3.646)	13.760***	(3.113)	7.488*	(3.971)
Class	18.735***	(2.136)	24.231***	(4.757)	−6.351***	(2.236)	−14.865***	(4.802)
Class × CRT = 1 or 2	–	–	−4.911	(5.584)	–	–	11.523**	(5.662)
Class × CRT = 3	–	–	−14.009**	(5.929)	–	–	13.749**	(6.275)
Constant	28.402***	(2.540)	25.494***	(3.165)	77.619***	(2.461)	81.148***	(2.922)
No. of observations	1200		1200		1169		1169	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.



(a) Multiple Price List 1 ($\Delta U = 1$ kWh, $\Delta EC = 1$) **(b)** Multiple Price List 2 ($\Delta U = 49$ kWh, $\Delta EC = 0$)

Fig. 2. Willingness-to-Pay for the More Energy-Efficient Appliance, by CRT. *Notes:* The points indicate the mean WTP for Multiple Price Lists 1 and 2, while the whiskers span the 95% confidence interval. *Class* and *No Class* denote the two experimental conditions, where efficiency classes are displayed or not displayed, respectively.

sentation of efficiency classes, but to a smaller extent (left panel of Fig. 2).

5. Summary and conclusions

To explore the impact of cognitive reflection on consumers' valuation of energy efficiency, we conducted a stated-choice experiment among around 3600 German household heads on the hypothetical purchase of refrigerators, thereby seeking to disentangle how cognitive reflection interacts with consumers' response to the two constituting elements of the EU energy label: energy efficiency classes and annual electricity usage.

Our findings highlight the importance of cognitive reflection for explaining consumers' valuation of energy efficiency. First, we find that consumers with a high level of cognitive reflection value energy efficiency more than those with low cognitive reflection levels. Second, we demonstrate that individuals with low cognitive reflection respond more strongly to the provision of efficiency classes than those with high cognitive reflection. Our results also indicate that displaying energy efficiency classes comes at a cost, as consumers with a low level of cognitive reflection pay less attention to the more detailed information on annual the electricity consumption rate of an appliance. Accordingly, for consumers with a low level of cognitive reflection, their willingness-to-pay (WTP) for energy efficiency does not continuously increase with energy efficiency, but exhibits jumps when energy efficiency classes change, for example from A+ to A++.

To sum up, our findings draw a nuanced picture of the EU label. On the one hand, the presentation of efficiency classes primarily influences the decision-making of individuals with a low level of cognitive reflection. As these individuals typically value energy efficiency less than individuals with higher cognitive reflection, the presentation of efficiency classes can be seen as a useful device for individuals with low cognitive reflection. On the other hand, our results suggest that presenting efficiency classes distracts attention from electricity consumption information and thus inhibits a comprehensive evaluation of energy efficiency. The relevance of such information substitution depends critically on the supply side and is moderate when producers mainly offer appliances that slightly exceed the efficiency class thresholds, as it is frequent practice. In addition, our findings on how class valuation and information substitution effects can potentially offset each other and help to rationalize why previous studies find only negligible effects of showing efficiency classes (Andor et al., 2019) and are thus important for understanding the effectiveness of energy labels.

A promising strategy to overcome information substitution is the provision of operating cost information on the EU label, which has been suggested by some recent studies (Andor et al., 2019, Andor et al., 2017 and Blasch et al., 2019). By reducing cognitive effort, information on operating costs simplifies investment decisions and mitigates the attention crowding-out effect of energy efficiency classes. Accordingly, we assume that such a modification of the EU label would increase the adoption of energy efficient appliances, in particular among consumers with low levels of cognitive reflection. In addition to testing this assumption, future research could also investigate whether providing cost information is a complement or a substitute to the presentation of energy efficiency classes.

Acknowledgements

We highly appreciate the helpful comments and suggestions by Colin Vance and gratefully acknowledge financial support by the German Federal Ministry of Education and Research (BMBF) within the Kopernikus project ENavi (grant 01LA1113A) and by the German Research Foundation (DFG) through CRC TR 224 (Project B07) and the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within Project A3, "Dynamic Technology Modeling".

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eneco.2019.104527.

References

Allcott, H., Greenstone, M., 2012. Is there an energy efficiency gap? J. Econ. Perspect. 26 (1), 3–28.

Allcott, H., Taubinsky, D., 2015. Evaluating behaviorally motivated policy: experimental evidence from the lightbulb market. Am. Econ. Rev. 105 (8), 2501–2538.

Andor, M., Gerster, A., Sommer, S., 2017. Consumer inattention, heuristic thinking and the role of energy labels. Energy J. 41 (1), 83–112, Ruhr Economic Papers #671.

Andor, M.A., Fels, K.M., 2018. Behavioral economics and energy conservation – a systematic review of non-price interventions and their causal effects. Ecol. Econ. 148, 178–210.

Andor, M.A., Gerster, A., Götte, L., 2019. How effective is the European union energy label? Evidence from a real-stakes experiment. Environ. Res. Lett. 14 (4), 044001.

Augenblick, N., Nicholson, S., 2015. Ballot position, choice fatigue, and voter behaviour. Rev. Econ. Stud. 83 (2), 460–480.

Bertoldi, P., Hirl, B., Labanca, N., 2012. Energy efficiency status report 2012. Eur. Comm. JRC Sci. Policy Rep. 136.

Blasch, J., Filippini, M., Kumar, N., 2019. Boundedly rational consumers, energy and investment literacy, and the display of information on household appliances. Resour. Energy Econ. 56, 39–58 https://doi.org/10.1016/j.reseneeco.2017.06.001.

Brounen, D., Kok, N., Quigley, J.M., 2013. Energy literacy, awareness, and conservation behavior of residential households. Energy Econ. 38, 42–50.

Carson, R.T., Louviere, J.J., 2011. A common nomenclature for stated preference elicitation approaches. Environ. Resour. Econ. 49 (4), 539–559.

Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. Psychometrika 16 (3), 297–334.

Destatis, 2017. Bevölkerung und Erwerbstätigkeit. Statistisches Bundesamt, Report ID 2010300167004.

Diekmann, A., Preisendörfer, P., 1998. Environmental behavior: discrepancies between aspirations and reality. Ration. Soc. 10 (1), 79–102.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2010. Are risk aversion and impatience related to cognitive ability? Am. Econ. Rev. 100 (3), 1238–1260.

Frederick, S., 2005. Cognitive reflection and decision making. J. Econ. Perspect. 19 (4), 25–42.

Gabaix, X., 2014. A sparsity-based model of bounded rationality. Q. J. Econ. 129 (4), 1661–1710.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: policy insights from economic theory and empirical evidence. Rev. Environ. Econ. Policy 8 (1), 18–38.

Hille, S.L., Geiger, C., Loock, M., Peloza, J., 2018. Best in class or simply the best? The impact of absolute versus relative ecolabeling approaches. J. Public Policy Market. 37 (1), 5–22.

Hoppe, E.I., Kusterer, D.J., 2011. Behavioral biases and cognitive reflection. Econ. Lett. 110 (2), 97–100.

Houde, S., 2014. Bunching With the Stars: How Firms Respond to Environmental Certification.

Houde, S., 2018. How consumers respond to product certification and the value of energy information. RAND J. Econ. 49 (2), 453–477.

Jaffe, A.B., Stavins, R.N., 1994. The energy-efficiency gap: what does it mean? Energy Policy 22 (10), 804–810.

Johnson, F.R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D.A., Bresnahan, B.W., Kanninen, B., Bridges, J.F., 2013. Constructing experimental designs for discrete-choice experiments: report of the ISPOR conjoint analysis experimental design good research practices task force. Value Health 16 (1), 3–13.

McFadden, D., 2017. Stated preference methods and their applicability to environmental use and non-use valuations. In: Contingent Valuation of Environmental Goods: A Comprehensive Critique. Elgar, Cheltingham, pp. 153–187.

Newell, R.G., Siikamäki, J.V., 2014. Nudging energy efficiency behavior: the role of information labels. J. Assoc. Environ. Resour. Econ. 1 (4), 555–598.

Oechssler, J., Roider, A., Schmitz, P.W., 2009. Cognitive abilities and behavioral biases. J. Econ. Behav. Organ. 72 (1), 147–152.

Olsthoorn, M., Schleich, J., Gassmann, X., Faure, C., 2017. Free riding and rebates for residential energy efficiency upgrades: a multi-country contingent valuation experiment. Energy Econ. 68, 33–44.

Peterson, R.A., 1994. A meta-analysis of Cronbach's coefficient alpha. J. Consum. Res. 21 (2), 381–391.

Stadelmann, M., Schubert, R., 2018. How do different designs of energy labels influence purchases of household appliances? A field study in Switzerland. Ecol. Econ. 144, 112–123.

Waechter, S., Sütterlin, B., Siegrist, M., 2015. The misleading effect of energy efficiency information on perceived energy friendliness of electric goods. J. Clean. Prod. 93, 193–202.