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Based on a stated-choice experiment among about 3,600 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 scores value energy efficiency less than those with high scores. Furthermore, we find that consumers with a low level of cognitive reflection respond more strongly to grade-like energy efficiency classes than to detailed information on annual energy use.

Keywords: Environmental certification; decision heuristics; energy-using durables.

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

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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 has 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 originating from a sample of around 3,600 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. Coupled 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 decision 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 received 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 information substantially increases the willingness-to-pay (WTP) for energy-efficient light bulbs, while the current EU label has no effect on WTP.

Few studies have investigated the mechanisms through which energy labels affect decision-making. One rare example is Blasch et al. (2017), 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. (2017) 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 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 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 Figure 1, the EU 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 European market.

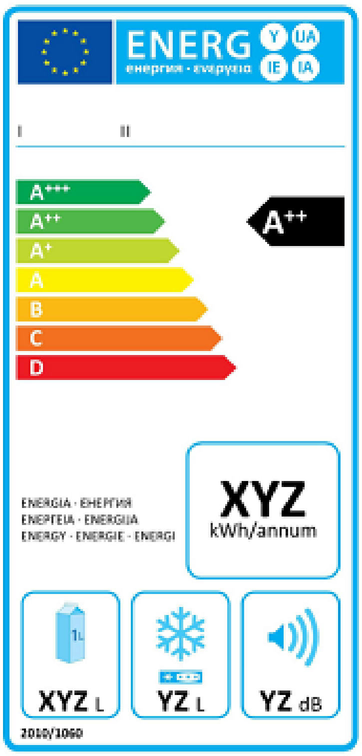


Figure 1: EU Energy Label for Refrigerators

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.

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

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 kilowatthours (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.

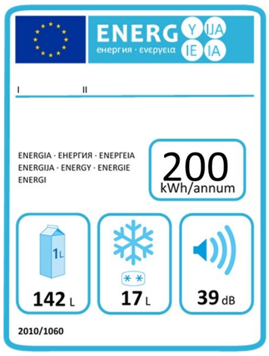
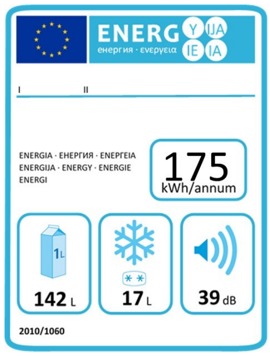
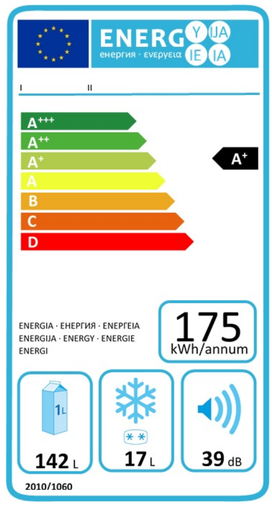
All choice sets included a benchmark refrigerator with an annual electricity consumption of 200 kWh (Alternative A). Varying the product attributes of Alternative B over the 12 choice sets allows us to trace out the demand curve over a range of electricity consumption values relative to Alternative A. 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 offered at the market. Our approach to primarily present hypothetical appliances is due to the fact that producers strategically respond to the EU label

[1]The choice sets are based on product data provided at the website of Media Markt, a large German retailer of electric appliances. 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 2: Illustration of the Choice Alternatives

NoClass Condition		Class Condition	
Alternative A	Alternative B	Alternative A	Alternative B
			
Price: 259 EUR	Price: 349/409 EUR	Price: 259 EUR	Price: 349/409 EUR

in that they do not vary the energy efficiency of appliances continuously, but in increments in order 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 conceived sets to each participant. In fact, robustness checks presented in Table A3 in the appendix show that our main results remain largely unchanged when only the first choice of each respondent is used for the estimations, so that choice fatigue does not appear to be an issue in our study.

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, called here 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. That is, 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

Table 3: Choice Sets Used For Multiple Price Lists

	Mutiple Price List I		Multiple Price List II	
Attributes	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)

choose between the more energy-efficient appliance B and the less efficient appliance A at eight purchasing price differences, ranging from -20 to EUR 120 – see Table A1 in the appendix for a detailed overview on the multiple price lists.

Multiple Price List 1 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.

The experiment was embedded in a survey that was conducted by the survey institute *forsa* using its household panel. (Information on the panel is available at `http://www.forsa.com/`.) 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, 3,608 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 were female and about one quarter graduated from college. Pro-environmental attitudes were measured by a variant of the Diekmann-Preisendörfer (1998) scale, which we normalized to unity.[3] As

[3] 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

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	2,773	2,813	2,733	-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**
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	3,549	1,772	1,777	–	–

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

becomes evident from Table A2, 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 cognitive reflection as low if a respondent answered no question correctly (CRT score=0) and as high if a respondent provided three correct answers (CRT score=3). Those respondents who answered either one or two questions correctly were assigned 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 differences in means, we cannot reject the null hypothesis of no difference across groups at the 5% sig-

(1951) Alpha of $\alpha = 0.762$, which is very similar to the mean Alpha for measuring attitudes in Peterson's (1994) meta analysis.

nificance level throughout. By contrast, as expected, 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 under 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 increases to 6.2 percentage points (not reported in Table 4), and hence more than triples, when we focus on choices between refrigerators that are offered on the 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 indistuingshable across the experimental 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:[4]

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

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. $(CRT = 1 \textit{ or } 2)_i$ and $(CRT = 3)_i$ 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 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 $(\Delta P = 150)_j$ 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

[4]We prefer using linear probability models, as the coefficients can be interpreted as marginal effects and the interaction terms are, in contrast to non-linear models, easy to interpret. As a robustness check, we also estimated a probit model, whose results, reported in Table A7 of the appendix, are very similar to those of the linear probability model.

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)
ΔP=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	4,701		4,701		4,782		4,782	
No. of respondents	1,590		1,590		1,612		1,612	

Note: ***, **, and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively. We have dropped all respondents who chose the option "I don't know" in all three choice sets (72 cases), as well as those who did not answer the CRT completely (275 cases).

variable ΔEC that equals unity if Alternative B in choice set j qualifies for a higher efficiency class:

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

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. Not surprisingly, the demand for the more energy-efficient appliance is lower when the price mark-up relative to Alternative A amounts to $\Delta P =$ EUR 150, rather than just EUR 90.[5]

To translate effect sizes into monetary terms, we calculate equivalent price metrics by divid-

[5]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 Class Condition and zero otherwise, is interacted with ΔU and ΔEC (see Table A4 of the appendix).

ing each coefficient estimate by the estimate of $\beta_P/150$, while standard errors are approximated using the Delta Method. The results, presented in 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. When assuming a 5% discount rate, as is done by Newell and Siikamäki (2014), the discounted lifetime value of an electricity saving of 1 kWh over 14 years is EUR 2.1. Accordingly, supporting the findings by Newell and Siikamäki (2014), we do not find evidence that – on aggregate – consumers undervalue energy efficiency.

Similar to the NoClassCondition, respondents that face the Class Condition are more likely to opt for the energy-efficient appliance when electricity savings ΔU are higher (see Specification 3 of Table 5). In addition, two effects deserve be to be highlighted: First, the large positive estimate of the coefficient of ΔEC, which is statistically significant at any conventional level, implies that displaying efficiency classes creates jumps in the adoption of more energy-efficient appliances at the class cutoff values even when energy savings are marginal, an effect that we henceforth denote *class valuation effect* (Andor et al., 2017).[6]

Second, the coefficient estimate on ΔU is significantly lower than that emerging from 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 NoClass Condition, for instance, the WTP for a permanent

[6]Given our experimental design, there are two jumps in the adoption of more efficient appliances, namely at those cutoff values that discriminate between A+++ and A++, as well as A++ and A+, respectively. While the estimates reported in Table 5 do account for the difference in both jumps, Table A5 in the appendix presents the results of a model where we split the class jumps, with findings similar to those of Table 5.

electricity saving of 1 kWh amounts to EUR 2.28 for respondents with the lowest CRT scores, but rises to EUR 4.53 $= 2.28 + 2.25$ and EUR 5.63 $= 2.28 + 3.35$ 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) $\times$ Δ EC and (CRT = 3) $\times$ Δ 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.[7] 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 an alternative elicitation method allows for testing the robustness of our results.

4.2. Multiple Price Lists

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

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

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. If Alternative A is chosen over the entire price range, WTP is set to -20. To investigate whether presenting efficiency classes has varying effects across respondents with different CRT scores, we include the interaction terms $Class \cdot (CRT = 1 \textit{ or } 2)$

[7] 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.

Table 6: Willingness-to-Pay for Differences in the Efficiency Class and Electricity Usage

	Multiple Price List I ($\Delta U = 1$ kWh, $\Delta EC = 1$)				Multiple Price List II ($\Delta U = 49$ kWh, $\Delta EC = 0$)			
	(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	1,200		1,200		1,169		1,169	

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

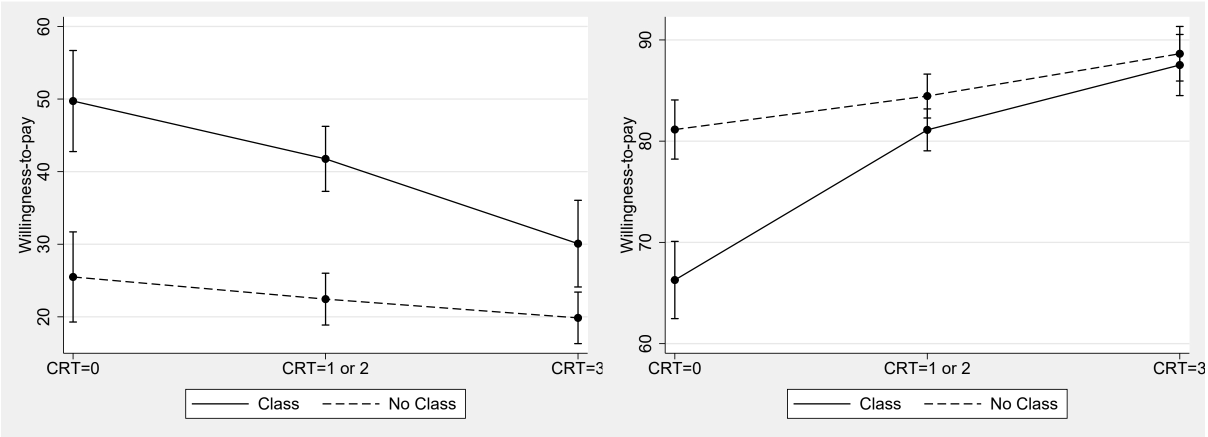
and $Class \cdot (CRT = 3)$.

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, 2,369 observations have been used for the analysis, the results of which are reported in Table 6. [8]

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 $Class \cdot (CRT = 3)$, which is statistically significant at the 5% level, 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 $Class \cdot (CRT = 3)$ 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

[8] As a robustness check, in addition to model (3), a Tobit model was estimated where the dependent variable is censored at EUR -20 and EUR 120, respectively. The results, reported in Table A8 of the appendix, are very similar to those presented in Table 6. Note also that the results are qualitatively the same when we control for socioeconomic characteristics (see Table A6 in the appendix).

Figure 2: Willingness-to-Pay for the More Energy-Efficient Appliance, by CRT



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

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.

the cognitive reflection than 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 both 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 CRT scores (see Specification 3 of Table 6). For instance, individuals with the maximum CRT score of 3 have a WTP of the energy-efficient refrigerator that is almost EUR 14 higher than the WTP for 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 facing the Class Condition value the energy use difference of 49 kWh by about EUR 6.4 less on average (see Specification 3 of Table 6). Furthermore, the positive coefficient estimates on the interaction terms $Class \cdot (CRT = 1 \ or \ 2)$ and $Class \cdot (CRT = 3)$ 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 (see Specification 4 of Table 6). Figure 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: Although all individuals tend to be influenced by the presentation of efficiency classes, those with a higher level of cognitive reflection are affected to a smaller extent than those with lower CRT scores (see left panel of Figure 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 3,600 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 usages. 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 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 critically depends on the supply side and is moderate when producers mainly offer appliances that slightly exceed efficiency class thresholds, as is frequent practice. In addition, our findings on how class valuation and information substitution effects can potentially offset each other 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 such 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. 2017). 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 investigate whether providing cost information is a complement or a substitute to the presentation of energy efficiency classes.

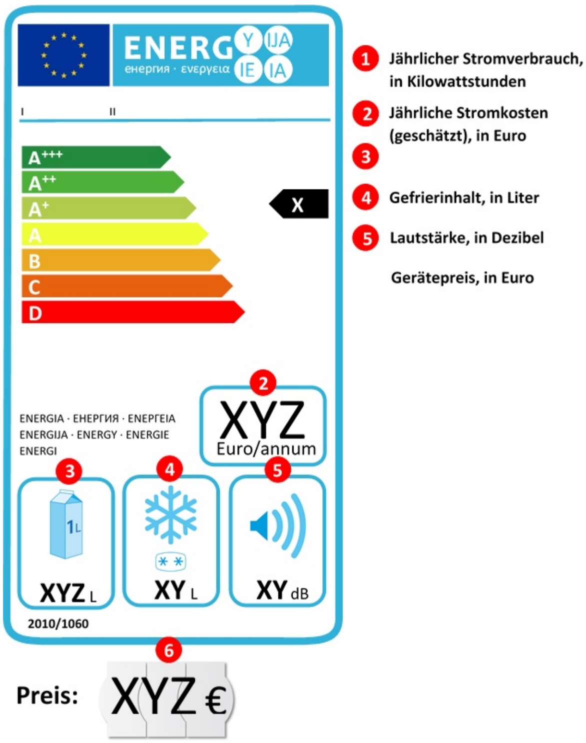
A. Appendix

A.1. Visualization of the Experiment

A.1.1. Binary-Choice Experiment

"Please imagine you are about to purchase a new refrigerator (e.g. like the one in the picture). Note that the average lifetime of a refrigerator in Germany is about 14 years."

"In the following, we will ask you to compare two refrigerators. The appliances are presented based on the EU-label and differ in the characteristics presented in the following figure:"



"We will show you three pairs of refrigerators. Please imagine that all characteristics that are not specified are identical (e.g. number of compartments, brand, etc.). Please choose the refrigerator that you would purchase if you needed to opt for one of them."

A.1.2. Multiple Price List

"In the following, you are required to choose between refrigerator A and refrigerator B. We only vary the price of refrigerator B. Please indicate which refrigerator you would choose at the given prices."

A.2. Cognitive Reflection Test

"The Cognitive Reflection Test (CRT) consists of the following three simple math problems that have an incorrect intuitive answer (Frederick, 2005):"

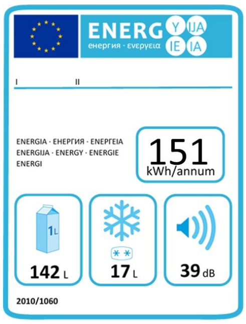
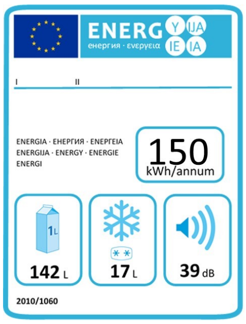
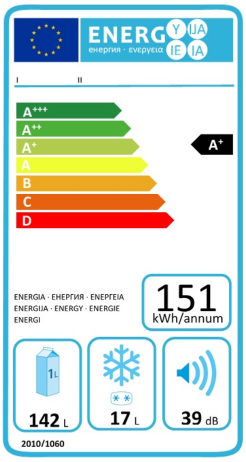
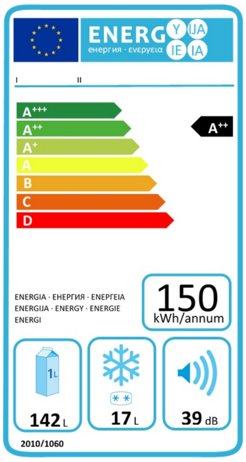
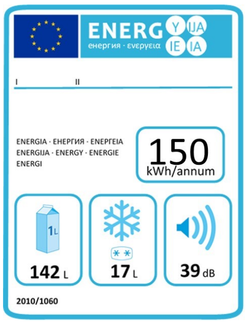
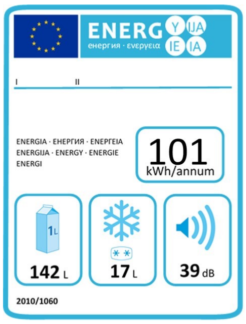
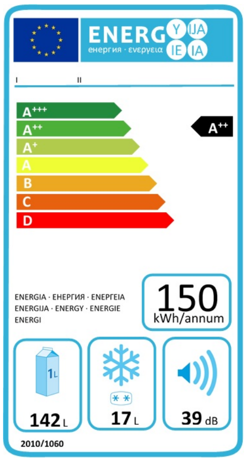
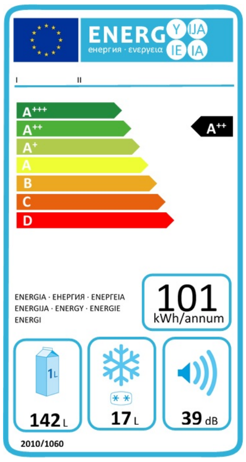
1. "A bat and a ball cost EUR 1.10 in total. The bat costs EUR 1.00 more than the ball. How much does the ball cost?"

2. “If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?”

3. “In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?”

A.3. Multiple Price Lists

Table A1: Overview of the Multiple Price List Experiment

Multiple Price List I			
No Class Group		Class Group	
Alternative A	Alternative B	Alternative A	Alternative B
			
Price: 319 EUR	Price: _______ EUR	Price: 319 EUR	Price: _______ EUR
Multiple Price List II			
No Class Group		Class Group	
Alternative A	Alternative B	Alternative A	Alternative B
			
Price: 319 EUR	Price: _______ EUR	Price: 319 EUR	Price: _______ EUR
Prices for Alternative B	299 319	339 359 379 399	419 439

A.4. Tables

Table A2: Comparison of our Estimation Sample with the Population of German Households

	Our Sample	Germany (2016)
1 Person household	0.273	0.411
2 Person household	0.463	0.340
3 Person household	0.138	0.123
Household with 4 or more members	0.126	0.127
East Germany	0.248	0.208
Household income > 4,700 EUR	0.109	0.128
Aged between 18 and 34	0.160	0.200
Aged between 35 and 64	0.533	0.524
Aged 65 and above	0.307	0.276
Woman	0.422	0.352
College degree	0.258	0.211

Source: Population data is drawn from Destatis (2017). This data source asks the main earner to complete the questionnaire, whereas we ask the household member who usually makes the financial decisions for the household.

Table A3: Linear Probability Estimations Results of the Binary-Choice Experiment Using First Choices Only

	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
CRT = 1 or 2	-0.013	(0.022)	-0.133**	(0.059)	0.019	(0.021)	-0.084	(0.059)
CRT = 3	0.023	(0.026)	-0.117	(0.073)	0.034	(0.027)	-0.090	(0.073)
Δ Usage	0.304***	(0.030)	0.190***	(0.050)	0.140***	(0.039)	0.020	(0.071)
ΔP=150 Euro	-0.127***	(0.019)	-0.127***	(0.019)	-0.088***	(0.019)	-0.088***	(0.019)
(CRT = 1 or 2) $\times$ Δ Usage	–	–	0.164**	(0.067)	–	–	0.183**	(0.091)
(CRT = 3) $\times$ Δ Usage	–	–	0.193**	(0.080)	–	–	0.163	(0.109)
Δ EC	–	–	–	–	0.176***	(0.031)	0.196***	(0.053)
(CRT = 1 or 2) $\times$ Δ EC	–	–	–	–	–	–	-0.046	(0.070)
(CRT = 3) $\times$ Δ EC	–	–	–	–	–	–	0.011	(0.088)
Constant	0.646***	(0.029)	0.728***	(0.043)	0.621***	(0.029)	0.694***	(0.046)
No. of observations	1,573		1,573		1,598		1,598	

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

Table A4: Linear Probability Estimations Results of the Binary-Choice Experiment – Fully Interacted Model

	Without Covariates		With Covariates	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Class	-0.014	(0.043)	-0.008	(0.049)
CRT = 1 or 2	-0.170***	(0.042)	-0.160***	(0.046)
CRT = 3	-0.236***	(0.051)	-0.209***	(0.056)
Class × (CRT = 1 or 2)	0.046	(0.057)	0.039	(0.063)
Class × (CRT = 3)	0.127*	(0.071)	0.117	(0.077)
Δ Usage	0.289***	(0.051)	0.314***	(0.061)
Class × Δ Usage	-0.102	(0.068)	-0.119	(0.079)
(CRT = 1 or 2) × Δ Usage	0.168**	(0.066)	0.160**	(0.075)
(CRT = 3) × Δ Usage	0.220***	(0.081)	0.177*	(0.090)
Class × (CRT = 1 or 2) × Δ Usage	-0.024	(0.088)	-0.013	(0.099)
Class × (CRT = 3) × Δ Usage	-0.093	(0.112)	-0.069	(0.121)
Δ EC	-0.052	(0.035)	-0.066*	(0.040)
Class × Δ EC	0.148***	(0.048)	0.164***	(0.054)
(CRT = 1 or 2) × Δ EC	0.051	(0.046)	0.058	(0.052)
(CRT = 3) × Δ EC	0.103*	(0.059)	0.131**	(0.066)
Class × (CRT = 1 or 2) × Δ EC	-0.036	(0.062)	-0.039	(0.070)
Class × (CRT = 3) × Δ EC	-0.074	(0.081)	-0.084	(0.087)
Female	–	–	0.032**	(0.012)
Household size=2	–	–	0.021	(0.015)
Household size=3	–	–	0.027	(0.022)
Household size>3	–	–	0.021	(0.028)
Children	–	–	-0.016	(0.024)
Homeowner	–	–	-0.003	(0.013)
College degree	–	–	0.032**	(0.013)
Income > EUR 4700	–	–	0.026	(0.018)
Age	–	–	0.002***	(0.000)
Pro-environmental attitudes	–	–	0.030***	(0.006)
ΔP=150 Euro	-0.143***	(0.008)	-0.146***	(0.009)
Constant	0.659***	(0.031)	0.510***	(0.046)
No. of observations	9,483		7,976	
No. of respondents	3,202		2,690	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A5: Linear Probability Estimations Results of the Binary-Choice Experiment – Detailed Efficiency Class Jumps

	Coeff.	Std. Err.
Class	0.007	(0.053)
CRT = 1 or 2	-0.172***	(0.051)
CRT = 3	-0.200***	(0.061)
Class × (CRT = 1 or 2)	0.044	(0.068)
Class × (CRT = 3)	0.078	(0.083)
Δ Usage	0.347***	(0.077)
Class × Δ Usage	-0.159	(0.100)
(CRT = 1 or 2) × Δ Usage	0.192**	(0.094)
(CRT = 3) × Δ Usage	0.153	(0.112)
Class × (CRT = 1 or 2) × Δ Usage	-0.025	(0.124)
Class × (CRT = 3) × Δ Usage	0.038	(0.149)
A+ to A++	-0.070*	(0.041)
A+ to A+++	-0.097	(0.059)
Class × A+ to A++	0.169***	(0.055)
Class × A+ to A+++	0.202***	(0.078)
(CRT = 1 or 2) × A+ to A++	0.054	(0.052)
(CRT = 1 or 2) × A+ to A+++	0.029	(0.073)
(CRT = 3) × A+ to A++	0.134**	(0.066)
(CRT = 3) × A+ to A+++	0.154*	(0.088)
Class × (CRT = 1 or 2) × A+ to A++	-0.038	(0.071)
Class × (CRT = 1 or 2) × A+ to A+++	-0.029	(0.097)
Class × (CRT = 3) × A+ to A++	-0.099	(0.088)
Class × (CRT = 3) × A+ to A+++	-0.185	(0.118)
Female	0.032**	(0.012)
Household size=2	0.021	(0.015)
Household size=3	0.026	(0.022)
Household size>3	0.021	(0.028)
Children	-0.016	(0.024)
Homeowner	-0.003	(0.013)
College degree	0.032**	(0.013)
Income > 4700 EUR	0.026	(0.018)
Age	0.002***	(0.000)
Pro-environmental attitudes	0.030***	(0.006)
ΔP=150 EUR	-0.146***	(0.009)
Constant	0.498***	(0.049)
No. of observations	7,976	
No. of respondents	2,690	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table A6: Willingness-to-Pay for Differences in the Efficiency Class and Electricity Controlling for Socioeconomic Characteristics Usage

	Multiple Price List I				Multiple Price List II			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Class	18.334***	(2.191)	23.352***	(5.001)	-7.121***	(2.370)	-15.927***	(5.420)
CRT = 1 or 2	-2.931	(3.049)	-0.492	(3.919)	8.156***	(3.106)	3.283	(3.950)
CRT = 3	-10.073***	(3.265)	-4.364	(3.903)	11.953***	(3.547)	5.737	(4.377)
Female=1	5.860**	(2.340)	5.839**	(2.346)	-0.343	(2.469)	-0.610	(2.475)
Household size=2	-1.451	(2.947)	-1.375	(2.952)	1.581	(2.939)	1.750	(2.936)
Household size=3	0.686	(4.056)	0.848	(4.046)	3.045	(4.349)	2.745	(4.341)
Household size=4	3.375	(4.942)	3.211	(4.955)	6.250	(5.277)	5.845	(5.262)
Children=1	-4.610	(3.950)	-4.520	(3.959)	-0.221	(4.338)	-0.005	(4.332)
Homeowner=1	-0.580	(2.517)	-0.464	(2.510)	4.401	(2.721)	4.214	(2.721)
College degree=1	-2.793	(2.419)	-2.620	(2.414)	6.417**	(2.582)	6.459**	(2.607)
Income $>$ EUR 4700 =1	-2.495	(3.194)	-2.341	(3.180)	0.077	(3.640)	0.284	(3.644)
Age	-0.024	(0.080)	-0.021	(0.080)	-0.093	(0.088)	-0.092	(0.087)
Class $\times$ (CRT = 1 or 2)	–	–	-4.670	(5.864)	–	–	11.431*	(6.273)
Class $\times$ (CRT = 3)	–	–	-11.571*	(6.153)	–	–	13.981**	(6.871)
Constant	27.188***	(5.483)	24.247***	(5.751)	77.450***	(5.611)	81.035***	(5.903)
No. of observations	1,074		1,074		1,029		1,029	

Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 % level and 10 % level, respectively.

Table A7: Analysis of Stated Choice Experiment (Marginal Effects of Probit Model)

	NoCLass Condition		Class Condition	
	Coeff.	Std. Err.	Coeff.	Std. Err.
CRT = 1 or 2	-0.011	(0.018)	-0.002	(0.017)
CRT = 3	-0.004	(0.022)	0.010	(0.021)
Δ Usage	0.384***	(0.017)	0.290***	(0.025)
Δ EC	–	–	0.082***	(0.017)
ΔP=150 Euro	-0.149***	(0.012)	-0.136***	(0.011)
No. of observations	4,701		4,782	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 % level and 10 % level, respectively.

Table A8: Tobit Model of the Willingness-to-Pay for Efficiency Class

	Multiple Price List I ($\Delta U = 1$ kWh, $\Delta EC = 1$)				Multiple Price List II ($\Delta U = 49$ kWh, $\Delta EC = 0$)			
	(1)		(2)		(3)		(4)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
CRT = 1 or 2	-5.612	(3.420)	-1.845	(4.469)	9.394**	(4.285)	1.321	(5.803)
CRT = 3	-12.938***	(3.547)	-4.400	(4.403)	16.939***	(4.996)	6.120	(6.605)
Class	21.126***	(2.537)	28.552***	(5.883)	-9.545***	(3.484)	-23.109***	(7.217)
Class × (CRT = 1 or 2)	–	–	-7.127	(6.789)	–	–	17.901**	(8.584)
Class × (CRT = 3)	–	–	-17.530**	(7.078)	–	–	23.212**	(9.954)
Constant	27.897***	(3.121)	23.975***	(3.922)	89.759***	(3.849)	95.488***	(4.712)
var(e.wtp)	1866.449***	(121.496)	1857.386***	(121.976)	3147.218***	(195.919)	3128.152***	(194.533)
No. of observations	1,200		1,200		1,169		1,169	

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

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