energies

Article

Tariff Menus to Avoid Rebound Peaks: Results from a Discrete Choice Experiment with Swiss Customers

Patrick Ludwig and Christian Winzer *

Center for Energy and the Environment (CEE), School of Management and Law,
Zurich University of Applied Sciences, 8401 Winterthur, Switzerland
* Correspondence: winc@zhaw.ch

Abstract: While automation helps to increase load-shifting, the combination of automation with time-of-use (TOU) or critical-peak prices (CPP) may lead to rebound peaks at the beginning of low-tariff periods which may exceed the original peak. Using a discrete choice experiment with a representative sample of 696 Swiss consumers, we find that a tariff menu including (i) a flat price with direct load control (DLC) and (ii) a time-of-use tariff without direct load control could avoid this problem. The majority (57%) of mostly younger customers, which could be interested in automation would likely sign up for a DLC with flat prices, while the remaining customers would either chose a TOU tariff with manual load control (28%) or avoid any form of load-shifting incentives (15%).

Keywords: demand response; demand side management; choice experiment; direct load control; dynamic electricity tariff; time-of-use tariff; electricity; willingness to accept; rebound peak

check for updates

Citation: Ludwig, P.; Winzer, C. Tariff Menus to Avoid Rebound Peaks: Results from a Discrete Choice Experiment with Swiss Customers. *Energies* **2022**, *15*, 6354. https://doi.org/10.3390/en15176354

Academic Editor: Surender Reddy Salkuti

Received: 8 June 2022
Accepted: 24 August 2022
Published: 31 August 2022

1. Introduction

In the 2016 Paris Agreement on climate change, many countries undertook a commitment to halve their greenhouse gas emissions by 2030 as opposed to 1990. In addition to increasing the efforts for energy conservation [1], to achieve this goal, the share of fluctuating renewables is expected to further rise within the following years. As a result, there will be an increasing need for flexibility to balance generation and demand and reduce the need for grid expansions. At the same time, the electrification of the heat and mobility sector and increasing penetration of smart meters will lead to a growing potential to provide this flexibility in the form of demand response [2–4].

Although some forms of demand response contracts, mostly static TOU tariffs, are commercially available in many countries, demand response has still not been widely adopted in the residential sector [5,6]. With an increasing spread of smart meters and automation this picture is likely to change. However, while automation is likely to increase the uptake of demand response contracts [7], the combination of automatic load control with TOU tariffs and other price signals may create unintended effects in the form of rebound peaks at the beginning of low price periods [8]. While the alternative approach of direct load control by utilities could avoid rebound peaks [9], it could be inhibited by a lack of trust in these organizations [10].

Within this paper, we will test which combination of price signals, automation approaches and measures for mitigating the associated risks should be used to maximize demand response uptake, while steering customers away from contracts that may lead to rebound peaks. For this purpose, we used a survey-based approach to elicit consumer preferences for DR tariffs. More specifically, we conducted a discrete choice experiment (DCE) on a representative sample of 1050 Swiss households. DCEs are a well suited and a widely applied methodology to elicit preferences for products or services where no market behavior is observable [11].

The remainder of this article is organized as follows. Section 1.1 provides a background on different forms of DR tariffs and on relevant literature. Section 2 describes the survey design and the econometric estimation strategy. The results are presented and discussed in Section 3. Section 4 concludes the paper.

1.1. Literature

Demand response programs can be grouped into price-based demand response, where time-varying electricity prices are used to encourage customers to shift their loads, and incentive-based demand response, where other forms of incentive are used for encouraging customers to shift their loads and/or allow third parties to control their loads. Price-based demand response approaches include time-of-use (TOU) pricing, critical peak pricing (CPP) and real-time pricing (RTP). While incentive-based demand response programs include, but are not limited to direct load control (DLC), load curtailment, demand bidding and critical peak rebate programs (CPR) [4,12,13].

The impact of demand response programs depends on the extent to which they achieve customer participation (i.e., tariff uptake), customer response (i.e., load adjustments) and persistence (i.e., avoiding drop-out or fatigue). While a small number of studies have assessed the persistence of demand response, the evidence is so far not conclusive [4]. In the following subsections we will therefore only discuss findings regarding customer participation and response for price-based (Section 1.1.1) and incentive-based (Section 1.1.2) demand response programs before summarizing the gap in the literature that we attempt to address with our study (Section 1.2).

1.1.1. Price-Based Demand Response

Studies regarding customer response to price signals find that customer peak demand is reduced more strongly if the peak to off-peak price ratio increases. Critical peak prices (CPP), which are typically associated with a higher peak to off-peak price spread thus tend to achieve larger reductions of peak load than other price-based approaches [4,14,15].

At the same time, many assessments regarding the participation in price-based demand response programs find, that CPP and RTP are less popular than TOU tariffs, because of concerns regarding excessive price risk, limited predictability and higher complexity of dynamic high-price periods [16–21]. Higher peak prices are thus both a concern, because they limit customer uptake, and a remedy, because they increase the response of those customers who sign up for the tariff.

Mitigation approaches to reduce the price risks for consumers without suppressing short-term price signals include the introduction of bill guarantees and or automation [20,21] to guarantee an automatic response to price signals and ensure that customers do not pay more on a CPP or RTP tariff than they would on a flat tariff or TOU tariff. In addition to increasing customer response to load-shifting signals, automation could also increase the participation of consumers in demand response programs [4,7,22].

1.1.2. Incentive Based Demand Response

Studies regarding the response of customers to incentive-based programs find that direct load control (DLC) achieves similar or higher peak reductions to time-based approaches such as (CPP), significantly higher than the peak reductions achieved by critical-peak rebates (CPR) [4]. This is not surprising, if we consider that DLC implies a 100% response of participating loads, as they are remote controlled by the utility or by an aggregator, while in case of CPR and other incentive-based programs, customers themselves are responsible for reducing demand during peak periods. As an additional advantage, DLC is likely to reduce the problem of determining appropriate "consumption baselines" [23,24] as customers are compensated for the possibility to remotely control their loads rather than for individual load reductions compared to a baseline. In the remainder of this paper, we therefore focus on DLC compared to price-based approaches without analyzing other incentive-based demand response approaches.

The results of studies regarding customer participation in direct load control programs are mixed. A recent review concludes that there is no significant difference between the uptake of DLC compared to price-based demand response programs such as TOU or CPP [4]. However, the combination of DLC with a flat tariff per kWh has been shown to be preferred by a majority of customers over any form of price-based demand response [7,21]. An important benefit of DLC could thus be the fact that it does not require time-varying price signals to incentivize optimal load-shifting. Remaining barriers for participation in DLC are the perceived complexity, effort, and dependency concerns/potential loss of control due to automation technologies (for automation in general), a lack of adequate compensation as well as customer distrust in the utility and concerns regarding data privacy (for the particular case of DLC) [10,25–27].

Mitigation measures which could increase the perceived control of automation include advanced notice and override options [5,25,28]. The perceived cost or effort of automatic load-shifting could be reduced by limiting the duration and/or frequency [5,28], as well as the season, time-of-day, or day of the week when the load may be shifted [29]. Complexity of automation could be reduced by providing technical support [30] as well as by specifying the automation parameters in a form that is easier to understand for consumers (such as guaranteed room temperature and battery charging levels instead of frequency and duration of load shifting). Measures to establish trust include the involvement of trusted actors, improved transparency, communication and accountability [13], as well improved data security and ultimately the automatic load control by customers themselves [30,31], e.g., through a home energy management system in their house. Depending on the device and the degree of comfort loss that is caused by DLC, customers expect a financial compensation of about 60 CHF/y or more [27,32].

1.2. Research Focus

While most of the risk mitigation measures in Sections 1.1.1 and 1.1.2 are uncritical, the automatic self-dispatch by customers, which was suggested in [30,31], could lead to unintended consequences. Achieving an efficient self-dispatch by consumers would require some form of time-varying prices. If price signals are provided in the form of TOU and or CPP prices, an automatic load response to the price signals could lead to rebound peaks [8].

Within this paper, we will test which combination of price signals, automation approaches and measures for mitigating the associated risks should be used to maximize demand response uptake, while steering customers away from contracts that may lead to rebound peaks.

To facilitate targeted marketing efforts, we will describe each customer segment with regards to its demographic and psychographic attributes.

2. Materials and Methods

To answer this question, we designed a survey, including an introductory section, a discrete choice experiment and a set of psychographic follow-up questions including one screening question. During the introductory section, we asked participants about their current tariff and experience with DLC, while the psychographic section contained 24 questions on a 7-point Likert-scale regarding the participants' personalities and their attitudes towards the environment and automation. In addition to that, we had access to the answers to 24 additional psychographic questions, which had been collected from the same respondents during the Swiss Household Energy Demand Survey (SHEDS) [33]. An overview of all psychographic questions, including the data source, is given in Table A1 in the Appendix A.

While the evaluation of answers for the Introduction and Psychographic sections is straightforward, the design, data collection and evaluation of the discrete choice experiment are described in more detail in Sections 2.1 and 2.2, followed by a description of our data collection process in Section 2.3.

2.1. Design of Discrete Choice Experiment

Discrete choice experiments (DCEs) are a common and widely applied approach in studying consumer preferences towards electricity contracts in energy economics [30,34,35]. DCEs are typically used to investigate individuals' valuations of products for which revealed preference data through actual purchasing behavior is not available [11]. Residential consumers usually select contracts which are described by a bundle of characteristics. Discrete choice experiments mimic such real-life choice situations by presenting several sets of alternatives and levels to the respondents from which they are asked to pick their preferred option.

The selection of attributes and attribute levels was based on a comprehensive design process. First, a literature review was carried out. Literature focusing on the value of lost load and direct load control revealed many contract attributes that can be used to reduce the cost and complexity and increase the perceived control of automation (cf. Section 1.1.2 above). Following several review rounds with experts from academia and the energy industry between October and December 2020, we decided to include pricing schemes and load control approaches (as the combination of self-dispatch with ToU tariffs may lead to rebound peaks), automation control parameters (as the benefit of different approaches had not yet been assessed), bill guarantees (to reduce price-risk without creating rebound peaks) and expected yearly compensation levels (so as to allow us to estimate the monetary value of the attributes). The resulting selection of attributes is described in Table 1.

Table 1. Attributes and levels of the discrete choice experiment.

Attributes	Levels	Description
Pricing scheme	Fixed rate, TOU, CPP	The timing and frequency of peak periods and the electricity price during these occasions.
Load control	Manual, Automated by EMS, Remote control by utility	Describes whether the electricity consumption is adjusted manually, automatically by an energy management system (EMS), or remotely by the utility
Automation control parameters	Comfort level, frequency and duration	Defines the control specifications according to which the automation/remote control works.
Bill guarantee	No guarantee, no loss, guaranteed	Defines whether the reduction in the yearly electricity bill is guaranteed. Without adequately changing electricity consumption to the pricing scheme, an increase in the yearly electricity bill is possible.
Expected savings (per year)	50 CHF, 100 CHF, 150 CHF, 200 CHF	On average, switching to the tariff and adjusting electricity consumption will lead to the following annual savings.

The pricing scheme was presented as the first attribute. With this attribute, respondents were asked to choose between an inflexible fixed electricity price, a TOU tariff and a flexible CPP tariff. As most respondents will not know these tariff approaches, we described the electricity price levels and the peak hours for each of these tariffs in two separate rows in the choice cards (see Table 2). The TOU tariff was presented by regularly occurring peak time with a medium price spread between peak (30 Rp./kWh) and off-peak hours (18 Rp./kWh). This type of tariff is currently the most widespread in Switzerland and should have been familiar to most respondents. A CPP tariff was described with a maximum of 50 peak periods per year and a larger price spread (18 Rp./kWh to 60 Rp./kWh). The rate of the fixed pricing scheme was chosen slightly below the current average electricity price in Switzerland (19 Rp./kWh). Together with the remote load control attribute this combination describes a DLC contract.

Table 2. Sample choice card.

Which Tariff Would You Choose?				
Attribute	Tariff A	Tariff B	Tariff C	Current Contract
Electricity price	19 Rp./kWh	PH: 30 Rp./kWh OPH: 18 Rp. kWh	PH: 60 Rp./kWh OPH: 18 Rp. kWh	
Peak hours	Never	Monday-Friday 16:00–20:00	50 days a year 16:00–20:00	
Load control	Remote Control by utility	Manual	Automated by EMS	
Automation Control parameters	Frequency and Duration	-	Comfort Level	
Bill guarantee	Guaranteed	No guarantee	No loss	
Expected savings	100 CHF	50 CHF	150 CHF	

The attribute regarding load control includes three different approaches. A manual adjustment of demand during peak periods, an automatic self-dispatch of loads using an energy management system (EMS) in the customers' premises, and a remote control by the utility (which corresponds to a DLC approach).

The attribute regarding control parameters described which types of control parameters would need to be specified by the customer in case of automatic load control by an EMS or remote load control by the utility. The respondents were asked to choose between specifying required comfort parameters (e.g., a minimal room temperature) or explicitly specifying the maximum frequency and duration of automatic load control measures.

The attribute bill guarantee included three levels. In case of the "no guarantee", an insufficient load reduction during high-price periods could lead to bill increases. In the case of the "no loss" option, customers were guaranteed that a switch to the new tariff would not result in bill increases. In case of the "guaranteed bill savings", customers were guaranteed that a switch to the new tariff would result in at least the savings specified by the last tariff attribute.

The expected savings attribute described the expected annual yearly savings which customers could realize by switching to the tariff. The exact amount of savings would depend on their reaction to price signals, as well as the bill guarantee (last attribute). The levels of expected savings varied between 50 CHF to 200 CHF and were calibrated based on synthetic load profiles from household load, electric vehicles, and heat pumps. In combination with grid utilization data and electricity prices provided by a medium sized distribution grid operator in Switzerland, the maximal load shift potential was estimated by calculating the shiftable load per household during the 50 highest grid utilization periods.

The DCE consisted of seven choice tasks per respondent. In each choice task, the respondents were asked to choose between three hypothetical DR electricity tariffs and a status quo option that indicated their current electricity contract (Table 2).

The DCE design was created using the software Sawtooth (choice-based conjoint functionality). For this study, the "Complete Enumeration" design option was chosen, which creates a nearly orthogonal design with minimal overlap. This means that the attribute levels are kept as different as possible within a choice task [36]. To avoid confronting participants with implausible attribute combinations, the occurrence of: electricity price = fixed-rate, load control = manual load control, and bill guarantee = guaranteed savings was prohibited within a tariff. Prohibiting illogical attribute combinations avoids introducing additional hypothetical bias [37].

2.2. *Evaluation of Discrete Choice Experiment*

To estimate the households' preferences based on the DCE, we used Lancester's attribute theory which assumes that the utility of a certain good is expressed as the sum of the part-worth utilities of the good's characteristics (attributes) [33]. Building on that, the random utility model introduced by [34] assumes that a customer n will choose a product (in this case electricity tariff) which provides the highest utility from a set of available tariffs j. The utility U_{nj} of tariff option j for customer n is expressed by the sum of the contract attributes X_{nj} and an unobserved error term ε_{nj}:

$$U_{nj} = \beta' X_{nj} + \epsilon_{nj} \tag{1}$$

where β is a vector of unobserved coefficients. The basic model for such applications is the conditional logit model which can easily be extended and tailored to the specific purposes of the study. Under the assumption that the error term ε_{nj} is independently and identically distributed (iid), the probability that the individual n chooses contract j is given by:

$$P_{nj} = \frac{\exp\left(\beta' X_{nj}\right)}{\sum_{j=1}^{J} \exp\left(\beta' X_{nj}\right)} \tag{2}$$

The standard conditional logit model brings some characteristics that limit the applicability for the choice of electricity contracts. The conditional logit model does not provide any information about taste variation around the average. The mixed logit model (MXL) overcomes these shortcomings by allowing individual specific parameters β_n which are assumed to vary around the population average parameter Θ with density $f(\beta_n | \Theta)$ [38]. The underlying distribution of Θ can take several forms, e.g., normal, lognormal, gamma, uniform or triangular. In line with the previously introduced literature, all non-monetary parameters were assumed to be normally distributed while the expected compensation was assumed to be lognormally distributed because a negative utility for the compensation attribute appears implausible [5,39].

Accounting for taste heterogeneity, the utility U_{njt} a customer n receives from choosing contract j in choice set t is described by:

$$U_{njt} = \beta_n' X_{njt} + \epsilon_{njt} \tag{3}$$

where ϵ_{njt} is the iid extreme value one (EV1) type error term. With β_n being unknown, the unconditional choice probability P_{njt} is defined as:

$$P_{njt} = \int \left(\frac{\exp\left(\beta_n' X_{njt}\right)}{\sum_{j=1}^{J} \exp\left(\beta_n' X_{njt}\right)} \right) f(\beta_n \mid \Theta) d\beta_n \tag{4}$$

As shown by [38], the equation cannot be evaluated analytically. Nevertheless, the choice probability can be estimated by using maximum likelihood simulation techniques based on Halton draws.

For this study, the monetary attribute ("Compensation") is linearly coded. The variables describing "Pricing scheme", "Load control", "Automation and control parameters" and "Bill guarantee" were dummy coded to avoid imposing a linear relationship between the attribute levels. This means that we created a separate column for each of the attribute levels, which either contained the value "1" or "0". For example, we created a column called TOU, which contains the value "1" for all tariff options including a time-of-use pricing scheme and the value "0" for all tariff options using another pricing scheme, etc. To avoid perfect collinearity between the independent variables, we chose the first attribute level as base-level and removed the corresponding dummy column from the regression. Each choice task includes a status quo option which represents the respondent's current electricity tariff. Including the status quo tariff is important to allow respondents to express their preferences based on their current electricity tariff [39]. An alternative specific constant (ASC) was included representing the status quo. An overview of the attribute levels and the resulting (dummy) variable names is provided in Table 3.

Table 3. Definition of variables.

Variable	Name	Type
Pricing scheme		
Fixed-rate	Base level	Base level
TOU	TOU	Dummy-coded
CPP	CPP	Dummy-coded
Load control		
Manual	Base-level	Base-level
Remote Control by utility	Utility	Dummy-coded
Automated by EMS	EMS	Dummy-coded
Automation Control parameters		
Comfort level	Base-level	Base-level
Frequency and Duration	DUR	Dummy-coded
Bill guarantee		
No guarantee	Base-level	Base-level
No Loss	NLSS	Dummy-coded
Guaranteed	GRNT	Dummy-coded
Expected Savings		
Compensation	COMP	Continuous
Status quo	ASC	Dummy-coded

The utility customer n receives from choosing contract j is thus expressed as:

$$\begin{aligned} U_{njt} = \beta_{n1}ASC_{njt} + \beta_{n2}TOU_{njt} + \beta_{n3}CPP_{njt} + \beta_{n4}Utility_{njt} + \beta_{n5}EMS_{njt} \\ + \beta_{n6}DUR_{njt} + \beta_{n7}NLSS_{njt} + \beta_{n8}GRNT_{njt} + \beta_{n9}COMP_{njt} \\ + \varepsilon_{njt} \end{aligned} \tag{5}$$

The MXL model was coded and estimated using the mixlogit STATA package by [40]. The standard model output reports the mean coefficient estimates as well as the standard deviation of the coefficients. For this study, simply being aware of the heterogeneity of preference is not sufficient. Therefore, we used a methodology proposed by [41] to derive individual specific coefficient estimates. The conditional mean calculation was performed using the STATA-mixlbeta command by [40].

To transfer the utility estimates to willingness-to-accept estimates we transform the parameters β_n to monetary space. This can be achieved by calculating the ratio between the non-monetary parameter of attribute k and the monetary parameter as follows:

$$WTA = -\frac{\beta_{nk}}{\beta_{n9}} \tag{6}$$

To further investigate the heterogeneity of preference, a cluster analysis was performed using the k-means clustering approach. The clustering was conducted on the conditional mean estimation. Socio-demographic, psychological and further energy-related variables were matched to the clusters. Finally, we performed a one-way ANOVA on the socio-demographic and psychographic variable to determine whether the mean of these variables is the same in all clusters.

2.3. Data Collection

Data were collected using an online survey with a sample drawn from the panel book of a professional survey company (Intervista) with over 100,000 panelists in Switzerland and Liechtenstein. A representative sample of the Swiss population in terms of age, gender, geographical location was selected. To increase response efficiency, the sample was limited to panelists who were fully or partly responsible for their household's electricity contract choices. Respondents were paid to complete the survey.

A pilot was performed to validate adequate attribute and level selection and tested whether the DCE was comprehensive to the respondents. A total of 50 respondents completed the pilot in November 2020 reporting no difficulties in understanding and answering the choice tasks. Consequently, only minor adjustments were performed prior to fielding the survey in January and February 2021. In total, 1050 respondents participated in the survey. Of these, 134 respondents did not finish the survey. To filter respondents who did not pay adequate attention, a screening question was included in the survey. A further 140 respondents who were not able to correctly answer the screening question were excluded. This resulted in 776 participants who successfully completed the survey. The sample was further refined by excluding respondents who answered exceptionally quickly or slowly (top and bottom 5% of completion times) and respondents who reported their choices to be random (n = 80). The final sample consisted of 696 respondents. The descriptive statistics of the final sample are presented in Table 4.

Table 4. Descriptive statistics of the respondents.

	Survey Respondents	Swiss Population
Socio-demographic characteristics		
Age (years) [42]	49.4	49.3
Household size [43]	2.3	2.2
Gender [42]		
Male	49.3%	49.6%
Female	50.7%	50.4%
Household income (gross CHF/month) [44]		
<3000	5.4%	7.1%
3000 to 4500	9.5%	10.1%
4501 to 6000	19.1%	12.2%
6001 to 9000	27.7%	25.0%
9001 to 12,000	22.1%	19.9%
>12,000	16.0%	22.3%
Education [45]		
Tertiary Education	47.0%	35.6%
Secondary Education	52.0%	45.4%
Compulsory Education	1.0%	19.0%
Living Environment [42]		
Urban areas	49.9%	63.0%
Agglomeration	28.1%	21.8%
Rural areas	21.9%	15.2%
Dwelling type		
Apartment building	57.7%	NA
Terraced house	16.2%	NA
detached or semi-detached house	26.0%	NA
Tenure [43]		
Owned	28.9%	36.3%
Rented	68.3%	60.3%
Other	2.8%	3.3%
Device Ownership		
Heat pump [46]	16.5%	17.9%
Electric vehicle [47]	5.0%	0.7%

3. Results

3.1. Attitudes towards Energy Related Topics

In the intro section of the survey respondents were asked about their current electricity contract (Figure 1). The majority (82%) of respondents reported that they are currently under a TOU tariff. As day and night tariffs are the default tariffs of most Swiss utilities these results seem reasonable. One fifth of the respondents (20%) stated that they currently have a DLC contract. As few utilities offer DLC contracts (mostly heat pump tariffs) this share appears to be surprisingly large.

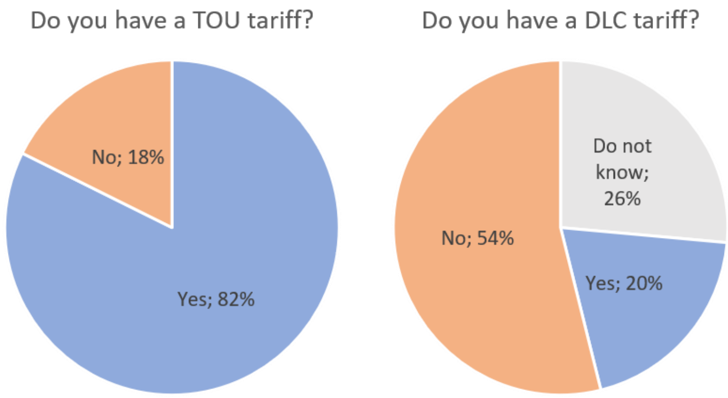

Figure 1. Current electricity tariff.

An overview of the psychographic scores is provided in Figure 2. The scores for each topic were calculated as the average value of a respondent's answers to all the associated questions from Table A1 in the Appendix A. With regards to automation, only 18% of respondents have concerns about unintended effects of automation, while slightly more (23%) of the respondents believe that automatic control of their household appliances could have a positive effect on their electricity costs and daily comfort. Regarding the environment, about half (53%) of the respondents have a positive attitude towards the environment, and an even larger share (63%) of respondents say that they are concerned about the future of the environment. Overall, 65% of respondents report a social expectation to support the environment. Regarding personality, most respondents (85%) in our sample could be regarded as satisficers, i.e., they are not worried about always finding the best possible solution. With regards to political orientation, 62% of respondents would describe themselves as oriented towards the left.

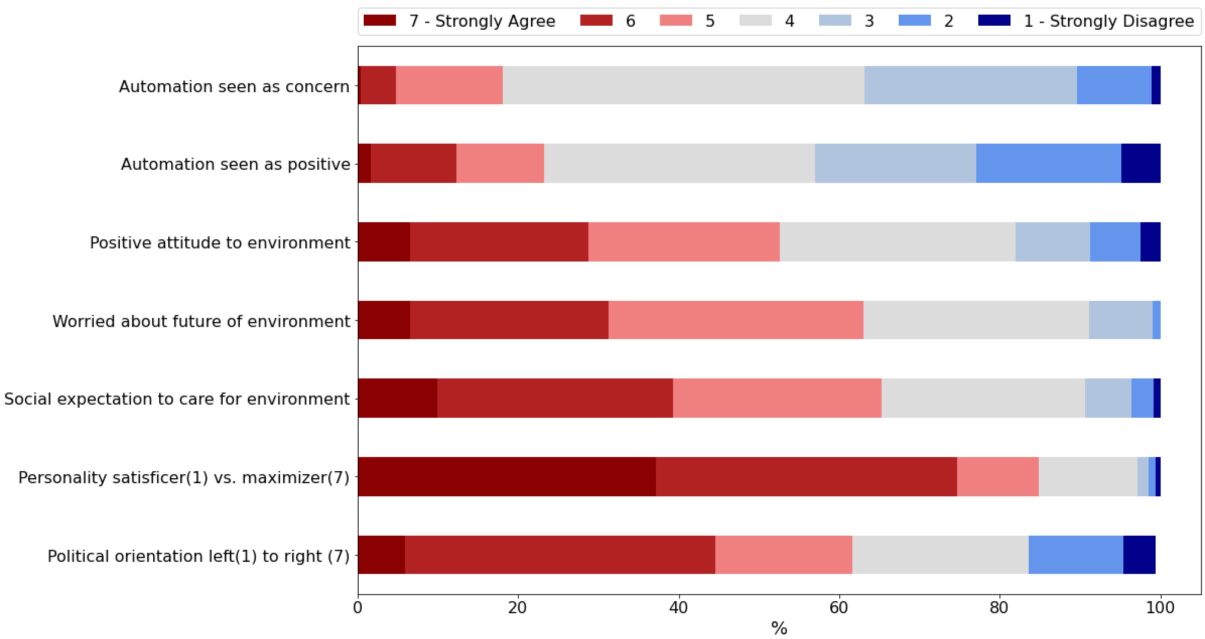

Figure 2. Response distribution of psychographic scores.

3.2. Preference for DR Tariffs

The results from the estimated models are presented in Table 5. We estimated three different models beginning with a conditional logit model (CL), followed by a mixed logit model (MXL) and a mixed logit model with correlated coefficients (MXL-C). All variables representing the contract attributes except for the monetary attribute were dummy coded. The variable names, their coding type and the base levels are presented in Table 3 above.

Table 5. Results of conditional logit (CL), mixed logit (MXL) and mixed logit model with correlated coefficients (MXL-C).

	CL			MXL			MXL-C		
Mean	**Coeff.**	**Std.Err.**	**WTA**	**Coeff.**	**Std.Err.**	**WTA**	**Coeff.**	**Std.Err.**	**WTA**
ASC	−0.541 ***	−0.12	−108.20 ***	−3.896 ***	−0.44	−308.80	−3.125 ***	−0.36	−209.73
TOU	−0.540 ***	−0.06	−108.00 ***	−1.364 ***	−0.14	−108.09	−1.199 ***	−0.15	−80.48
CPP	−1.079 ***	−0.07	−215.80 ***	−2.566 ***	−0.17	−203.35	−2.355 ***	−0.17	−158.05
EMS	−0.007	−0.07	−1.40	−0.266 *	−0.12	−21.09	0.263	−0.17	17.67
Utility	−0.112	−0.07	−22.40	−0.428 ***	−0.11	−33.95	0.054	−0.16	3.64
DUR	−0.033	−0.03	−6.60	−0.135	−0.07	−10.73	−0.029	−0.08	−1.95
NLSS	0.174 ***	−0.04	34.80 ***	0.258 ***	−0.07	20.44	0.362 ***	−0.08	24.31
GRNT	0.406 ***	−0.05	81.20 ***	0.665 ***	−0.1	52.69	0.679 ***	−0.11	45.61
COMP	0.005 ***	0		0.013 ***	0		0.015 ***	0	
Std.Dev.				**Coeff.**	**Std.Err.**		**Coeff.**	**Std.Err.**	
ASC				4.857 ***	−0.46		2.938 ***	0.41	
TOU				2.462 ***	−0.14		2.707 ***	0.21	
CPP				2.646 ***	−0.17		2.697 ***	0.19	
EMS				1.340 ***	−0.12		2.425 ***	0.19	
Utility				1.198 ***	−0.11		2.44 ***	0.19	
DUR				0.752 ***	−0.12		0.687 ***	0.15	
NLSS				−0.418 **	−0.14		0.642 ***	0.16	
GRNT				1.427 ***	−0.11		1.167 ***	0.15	
COMP				0.021 ***	0		0.029 ***	0	
Observations		19,488			19,488			19,488	
N		696			696			696	
ll		−6025.735			−4590.92			−4390.71	
aic		12,069.47			9217.839			8889.41	
bic		12,140.368			9359.635			9314.798	
chi2		565.718			2869.631			3270.061	

* $p<0.05$, ** $p < 0.01$, *** $p < 0.001$.

In general, the models that allow for preference heterogeneity perform better than a simple CL model when comparing the log likelihood, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Together with the highly significant standard deviations in the MXL models this indicates the presence of heterogeneity. The prediction hit rates of all models are 45% meaning that the models perform better than any random model that would have a 25% chance to predict the choice in any of the choice occasions.

The choice between the two models that allow for preference heterogeneity MXL and MXL-C model is more difficult since the information criteria are only slightly better in the MXL-C model. From a theoretical perspective, an MXL-C should fit a data set better when the parameter estimators are correlated. With respect to dynamic power contracts this assumption seems valid, since it seems reasonable to assume that participants who prefer one attribute that describes a DR tariff are likely to have a positive attitude towards other attributes describing a DR tariff. Our calculation of the Willingness-to-Pay (WTP) values we report in this section is therefore based on the coefficients of the MXL-C model. Boxplots of the resulting WTP values are shown in Figure 3.

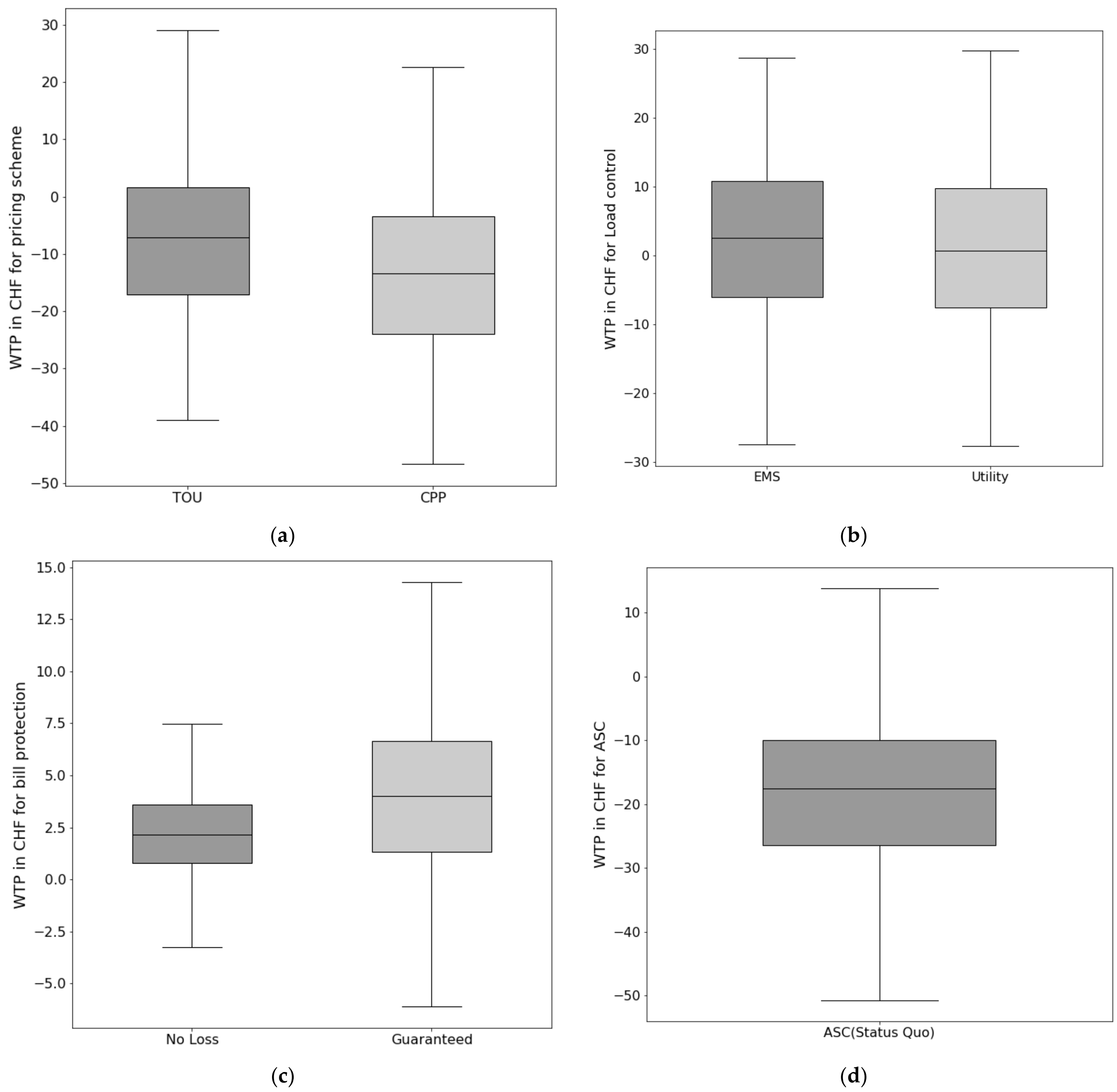

Figure 3. WTP distribution of the MXL-C model for: (**a**) pricing scheme, (**b**) load control approach, (**c**) bill protection and (**d**) ASC parameters.

The significant coefficients in all different models show the expected signs. The more dynamic tariff schemes TOU and CPP as well as the automated control by the utility show a negative sign across all models, which means that the presence of one of these attributes makes the alternative less attractive to consumers. In contrast, the attributes regarding bill protection and compensation show a positive sign. In addition, the attributes for pricing scheme (TOU and CPP), bill protection (no loss and guaranteed) as well as compensation are significant across all models.

In terms of the pricing scheme, the results indicate that respondents prefer an easy and predictable fixed pricing over TOU and CPP pricing. The parameter for TOU is significant at the 1% level and shows a negative sign. On average, consumers require a compensation of 7 CHF [$\pm 2\ CHF$] per month to choose a TOU tariff over a fixed tariff.

As most of the Swiss households are currently under a TOU tariff these findings indicate that even consumers who are familiar with the concept of time dependent prices tend to have preference towards a uniform tariff. Although, it must be mentioned that the framing chosen in this survey described shorter peak time periods and higher peak time prices compared to the typical day and night tariffs currently present in Switzerland. As expected, CPP as the most flexible tariff scheme presented in this experiment shows a larger negative sign whilst being highly significant. To choose CPP tariffs over fixed tariffs respondents required a monthly compensation of 13 CHF [± 4 CHF]. As the fixed-pricing option only occurred in combination with EMS or utility load control level in the choice set, these results indicate that consumers prefer incentive-based DR schemes.

The influence of the presence of technology described by the load control attribute is not significantly different from zero in the CL and MXL-C model. Although, the control by EMS is associated with a positive WTP of 1 CHF [± 2 CHF] per month in the MXL-C model, the coefficients for EMS in the MXL model have a negative sign. Therefore, it must be concluded that the influence of the control by EMS is not clear. The estimates for control by utility are not significantly different from zero across all models. One possible explanation is that the presence of technology can be beneficial to some participants as less frequent user interaction is necessary [20], but at the same time could be disadvantageous to other participants due to perceived lack of control [13]. The large heterogeneity in this attribute supports this possible explanation. Consequently, the automation control parameter attributes are also not significantly different from zero across all models. Potentially, these findings indicate that respondents had difficulties understanding this attribute as it appears to be the most abstract one.

In contrast, including bill protection mechanisms to DR tariffs has a significant positive effect on participants utility. Respondents are willing to pay on average 2 CHF [± 1 CHF] per month to not pay more than under their current electricity tariff. As expected, the magnitude is higher when participants receive a guaranteed discount on their electricity bill. Participants average WTP is 4 CHF [± 1 CHF] per month.

The parameters of the ASC show a negative sign with a larger magnitude in the MXL model. In addition, the parameter is statistically significant at the 1% level. This suggests that participants gain utility from choosing any of the DR tariffs meaning that on average consumers are open for these newly introduced tariffs. On average, participants required a monthly compensation of 17 CHF [± 6 CHF] to stay with their current electricity tariff. Nonetheless, the ASC shows a highly significant and large magnitude standard deviation, indicating a large preference heterogeneity around the status quo. This indicates that there are respondents who prefer the status quo and respondents who would prefer to change to a new electricity tariff in the sample.

3.3. Heterogeneity of Preferences

To widely deploy DR tariffs, it is beneficial to understand whether some customer segments are more open towards dynamic electricity tariffs than others. To identify different costumer segments, we used the k-means algorithm on the conditional means utility estimates. The k-means algorithm assigns a subset of n observation to k clusters such that the within-cluster sum of squares (WCSS) is minimized. The algorithm requires the definition of the number of clusters as an input. To determine the number of clusters we calculated the WCSS for different numbers of clusters and chose the k where the efficiency gain by adding one more cluster was low. Based on this method, also referred to as the elbow method, we chose four clusters (Figure A1 in the Appendix A).

Based on their preference structure, survey respondents are distributed 24% (167) in Cluster 1, 33% (229) in Cluster 2, 28% (194) in Cluster 3, and 15% (106) in Cluster 4. The preference structure of the clusters is shown in Figure 4. It is evident that the preferences differ between the clusters, especially for the attribute categories of ASC, pricing scheme and load control. These attributes showed significant and high standard deviation in Section 3.2. The preference structure differences are much smaller for the attribute categories of control parameter, bill guarantee and expected compensation. This pattern is also confirmed by the results from Section 3.2, in which these attributes showed a significant standard deviation, but one that was considerably lower in magnitude.

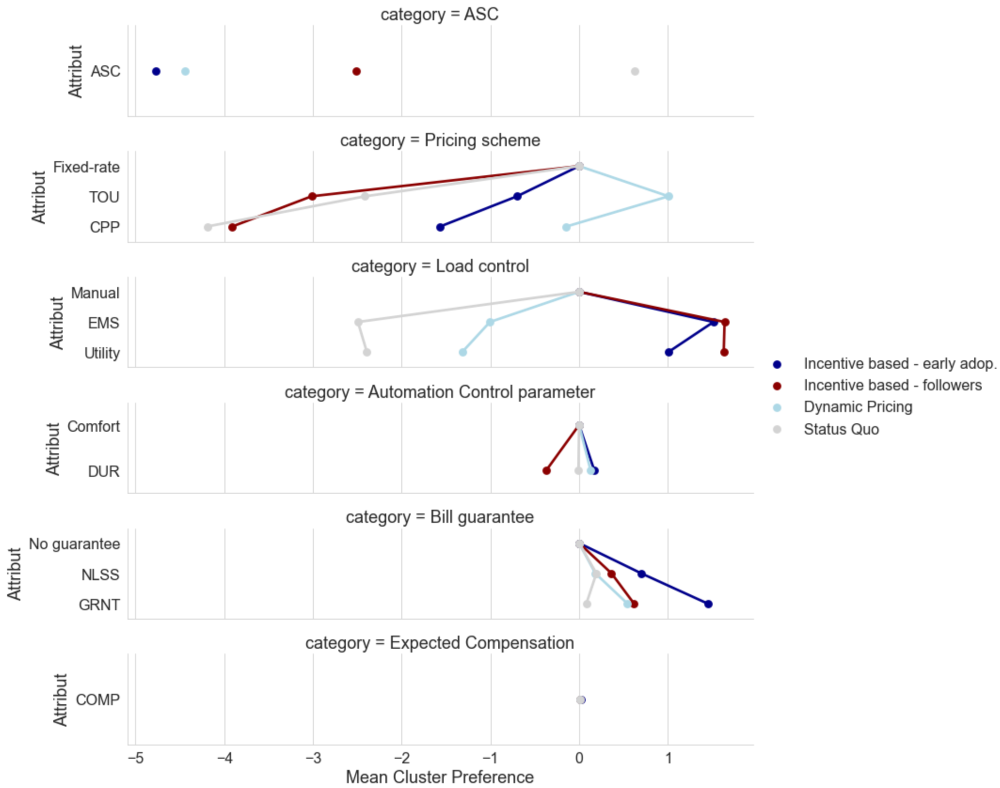

Figure 4. Cluster analysis of conditional mean preferences.

Cluster 1 is characterized by a strongly negative mean valuation parameter for the ASC. This indicates a general openness to DR tariffs. With respect to the pricing scheme, this cluster shows preferences for fixed-rate pricing schemes. Regarding the load control attribute, this cluster reveals above-average preferences for automatic control by an EMS. Likewise, control by the utility is preferred over manual control. The preference structure of Cluster 2 shows a very similar shape to Cluster 1. Respondents in this cluster reveal a negative preference for the ASC. However, the parameter shows a lower magnitude compared to Cluster 1 and to the full sample. This means that respondents in Cluster 2 are less likely to choose a DR tariff or in other words, require a higher compensation to opt for one of the DR tariffs. With respect to the pricing scheme attribute, it appears that Cluster 2 indicate strong preferences for a fixed-rate price. However, the aversion to dynamic pricing schemes is higher than in Cluster 1, which is expressed by the strongly negative valuation parameters. Cluster 2 also shows strong preferences for automatic load control by an EMS or direct load control by the utility. However, compared to Cluster 1, Cluster 2 is indifferent between these two options. Clusters 1 and 2 each show a preference structure that can be described as a preference for incentive-based tariffs. Due to the lower compensation demands of Cluster 1, this group can be described as early adopters and Cluster 2 can be described as followers due to the higher compensation requirements.

Respondents from Cluster 3 reveal a smaller than average preference towards the status quo option compared to the entire sample. In terms of pricing scheme, the mean valuation for a TOU scheme has a positive sign and a slightly negative sign for CPP pricing systems. On the other hand, this cluster has a strong aversion to automatic control of appliances. Accordingly, this cluster can be described as a group with preferences regarding price-based incentive mechanisms, especially with preferences for TOU. Therefore, we call this group "dynamic pricing".

In contrast to all groups described so far, respondents from Cluster 4 show a strong preference for the ASC and thus for their status quo electricity contract. Moreover, this cluster requires a significant compensation to accept any type of dynamic pricing or automation. This means that respondents in this group were not willing to accept a DR tariff in the DCE in return for the offered compensation. Accordingly, this cluster can be described as a customer group with strong preferences for the "status quo".

The characteristics of the clusters are shown in Table 6. Only those socio-demographic and psychographic variables are presented whose mean values differed between the clusters at the 5% significance level. Overall, a small number of the variables that was tested show a significant difference in means. While the differences between Cluster 1 to Cluster 3 are rather small, Cluster 4 ("Status Quo") has a smaller proportion of respondents in the age group 20–39 and a larger proportion in the age groups above 40. In addition, the proportion of students in this group is smaller than in the other groups.

Table 6. Conditional mean preferences and characteristics for each cluster.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster Name	**Incentive Based—Early Adopters**	**Incentive Based—Followers**	**Dynamic Pricing**	**Status Quo**
N	167	229	194	106
ASC	−4.77	−2.52	−4.44	0.62
TOU	−0.70	−3.02	1.01	−2.41
CPP	−1.57	−3.91	−0.14	−4.19
EMS	1.51	1.64	−1.00	−2.49
Utility	1.00	1.63	−1.32	−2.39
DUR	0.17	−0.37	0.13	−0.01
NLSS	0.70	0.37	0.18	0.19
GRNT	1.45	0.62	0.54	0.08
COMP	0.03	0.01	0.01	0.01
Socio-demographics				
Age 20–39 ***	0.43	0.39	0.36	0.17
Age 40–64 *	0.41	0.41	0.38	0.57
Age 65–79 *	0.16	0.17	0.25	0.26
Student/Pupil **	0.14	0.07	0.08	0.04
Psychographics				
Automation seen as concern ***	3.29	3.52	3.75	4.31
Automation seen as positive ***	4.98	4.73	4.41	3.89
Positive attitude to environment **	5.06	4.94	5.13	4.63
Political Orientation (1 Left; 8 Right) **	4.59	4.99	4.54	4.83

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

While only two socio-demographic variables show significant results, the differences regarding psychographic variables are larger. However, the differences here are also largest for Cluster 4. This group shows the highest concerns regarding automation and the lowest score regarding a positive attitude towards automation and regarding a positive attitude to the environment. Respondents in Cluster 2 tend to be oriented more to the left than respondents in the other clusters.

3.4. Tariff Adoption

Based on the average utilities of different contract attributes for each respondent cluster from the previous section (Table 6), we have calculated the expected utility of different tariff designs for each cluster in Figure 5. The utility which a respondent cluster attaches to a contract is calculated as the sum of utilities for the respective respondent cluster and contract attributes and is described in more detail in Appendix B. Many energy suppliers nowadays offer a menu including a flat-tariff (which does not enable automatic load control) and a TOU tariff (which could be combined with manual load control, or automatic load control by an EMS or by the utility). This corresponds to the first four tariff options in Table A2. In Figure 5, we have highlighted the tariff approach, which the customers from each cluster would prefer in that case using a red dot. While customers from Cluster 2 and Cluster 4 are unlikely to sign up for a TOU tariff, and customers from

Cluster 3 would prefer approach 2 (TOU, manual), the customers from Cluster 1 are likely to choose tariff approach 3 (TOU, EMS), which may lead to rebound peaks.

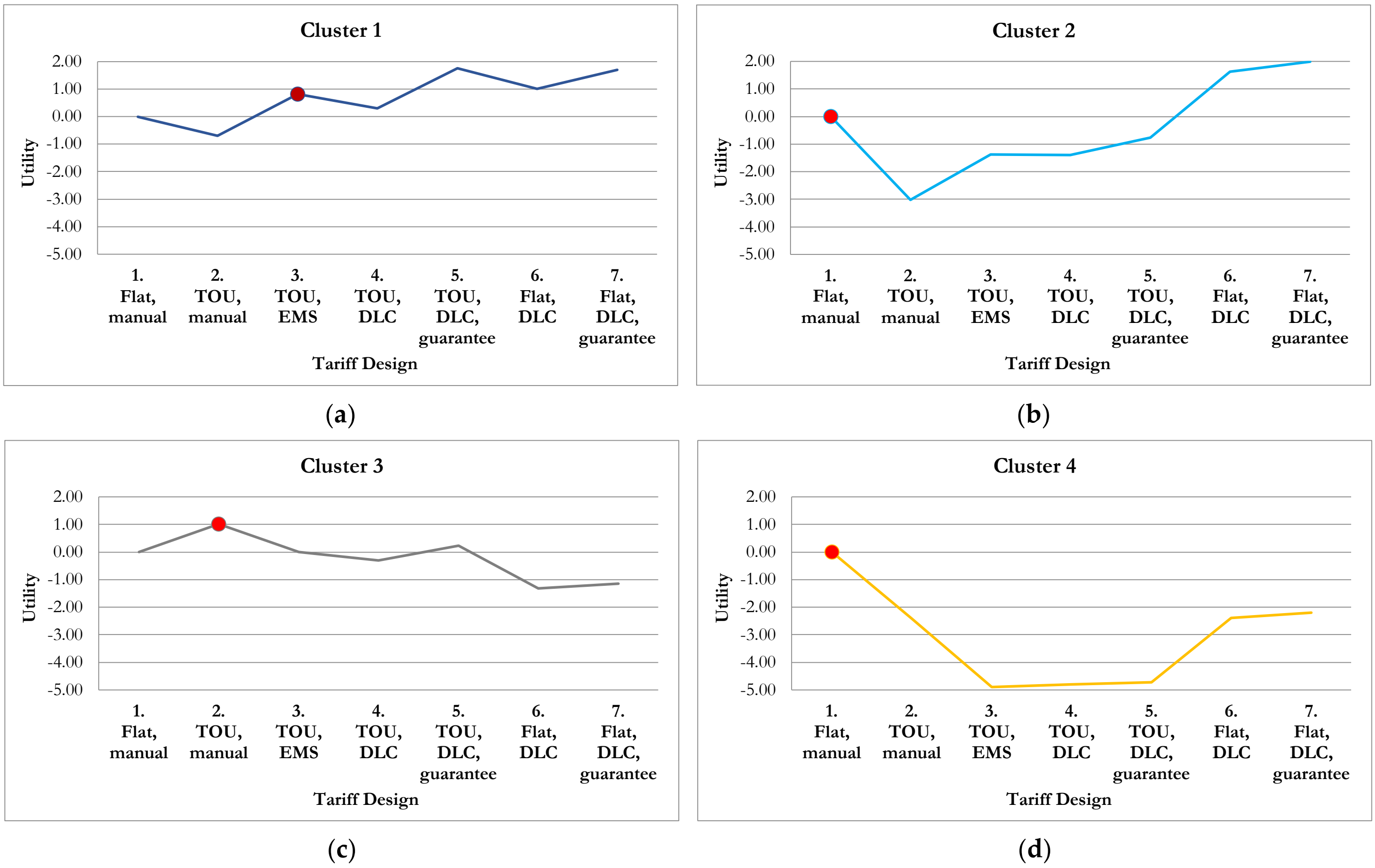

Figure 5. Expected average utility of different tariff designs for customers from: (**a**) Cluster 1, (**b**) Cluster 2, (**c**) Cluster 3 and (**d**) Cluster 4. Red dots indicate which of the tariff designs 1–4 is preferred.

To avoid this, energy suppliers could include any of the tariffs 5 to 7 in their tariff menu, as each of them is associated with a higher utility for Cluster 1 than tariff approach 3. Looking at the utility for Cluster 2, an important advantage of tariffs combining flat prices and DLC (tariff designs 6 and 7) could be that they increase the chances of tariff uptake by consumers from Cluster 2, who would otherwise not sign up for DLC or dynamic prices. The preferred choice of customers from Cluster 3 and 4 would not be affected by the additional availability of tariff 6 and 7. Customers from Cluster 3 would not react because they prefer manual load control with TOU prices over direct load control, while customers from Cluster 4 do not value the additional offer because they are averse to any form of load shifting incentives.

A tariff menu combining TOU prices and flat tariffs with DLC could thus be well suited to maximize demand response uptake, while avoiding rebound peaks.

4. Conclusions

Automation can increase the participation of consumers in demand response programs and their response to load-shifting signals. However, the combination of automation with TOU and or CPP price signals may lead to unintended consequences in the form of rebound peaks.

An effective solution to avoid rebound peaks while maximizing demand response uptake could be to offer a menu including (i) direct load control with a flat price signal and (ii) time-of-use tariffs without automatic load control. Customers who prefer an automatic control of their devices through an energy management system (Cluster 1) are likely to prefer load control by the utility or an aggregator with a flat price signal. Customers who prefer time-of-use tariffs over flat price signals (Cluster 3) on the other hand, seem to have a strong preference for manual load control, so that they are unlikely to use automatic load control by an energy management system.

Bill guarantees and compensations could be used to further increase the attractiveness of direct load control tariffs. However, in line with the findings from other studies [21], our results indicate that they may not be required as the benefit of switching to a flat energy price alone could be sufficient to convince those customers that are open for energy management systems (Cluster 1) to accept direct load control by the utility or an aggregator.

With regards to customer segments, we found that 57% of customers—who tend to be students or younger than 40—are open to automation (Cluster 1 and Cluster 2) because they find it easy to use, expect bill savings, and are less concerned about negative consequences of automation. At the other end of the spectrum, 15% of customers (Cluster 4)—who are usually older than 40 and not studying—are neither open to automation nor to dynamic prices, because they are less optimistic about the ease-of-use and economic benefits of automation and are afraid of losing control or suffering discomfort. In between these two extremes, about 28% of the customers (Cluster 3) are open to time-of-use prices, but not automation, potentially due to concerns about the environment—which are slightly higher for this group than for any other group—in combination with less optimism and more concerns regarding the impacts of automation than the first two clusters.

The analysis in this paper has been focused on tariff menus to avoid rebound peaks. Apart from that there are many other aspects that need to be considered for an optimal approach to demand response. For example, the efficiency of DLC depends on the incentives of the entity that controls the load. Aggregators that are facing competition may be more likely to share system benefits with their customers than monopolist distribution grid operators. On the other hand, while aggregators may have an incentive to employ flexibility in a way that maximizes value, they will only dispatch loads in a grid-friendly manner if they are provided with appropriate financial incentives, for example, through scarcity price adders or local flexibility markets. In addition to that, the implementation of a tariff menu also requires several practical considerations, such as the deployment of appropriate metering and control infrastructure which needs to be carefully assessed. For example, many of the first generation smart meters that were deployed in the UK turned dumb when suppliers were switched and so that they will need to be replaced by second generation of smart meters [48]. Control infrastructure required by DLC will increase cost and complexity compared to dynamic price signals.

While our findings are mostly in line with the literature, it must be noted that the results are based on hypothetical tariffs, which only include a selection of real-world tariff attributes. In addition, the choice of tariffs did not have financial or other consequences for participants. We thus expect the preference for the status quo to be much more pronounced in case of real switching decisions than in our survey-based choice experiment. In future research, the validity of our results should therefore be tested in real-world experiments. In addition to that, our choice experiment only included customers from Switzerland. Findings may thus not be representative for customers in other countries.

Author Contributions: Conceptualization, P.L. and C.W.; methodology, P.L. and C.W.; software, P.L.; validation, P.L. and C.W.; formal analysis, P.L.; investigation, P.L.; data curation, P.L.; writing—original draft preparation, P.L. and C.W.; writing—review and editing, P.L. and C.W.; visualization, P.L. and C.W.; supervision, C.W.; project administration, P.L. and C.W.; funding acquisition, C.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Swiss Federal Office of Energy (SFOE), Project Number: SI/501899-01. Open access funding provided by ZHAW Zurich University of Applied Sciences. The authors alone are responsible for the conclusions.

Institutional Review Board Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

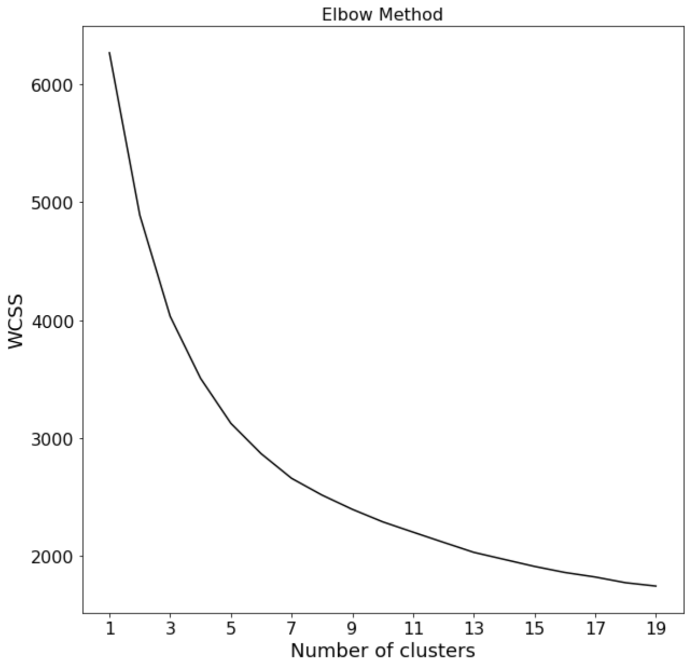

Figure A1. Elbow method.

Table A1. Psychographic scores, corresponding questions, and survey where the question was asked.

Psychographic Score	Associated Questions (7-Point Likert Scale)	Survey
Automation seen as concern	The amount of my electricity bill is out of my control.	Current survey
Automation seen as concern	I am afraid that automatic control of my household appliances will affect my daily habits and well-being.	Current survey
Automation seen as concern	I fear that a malfunction of the automatic control of my household appliances will significantly affect my comfort.	Current survey
Automation seen as concern	I fear that automatic control of my appliances will reveal personal information.	Current survey
Automation seen as concern	Automatic control of appliances may increase my electricity costs.	Current survey
Automation seen as positive	Automatic control of household appliances is helpful in furthering the development of renewable energy.	Current survey
Automation seen as positive	It is easy for me to understand new technologies like an energy management system for the automatic control of my household appliances.	Current survey
Automation seen as positive	If I allow automatic control of appliances, I will save money because no manual intervention is necessary.	Current survey
Automation seen as positive	If I allow automatic control of appliances, I will save money.	Current survey
Positive attitude to environment	I feel PROUD when I act in an environmentally friendly manner.	SHEDS
Positive attitude to environment	I feel HAPPY when I conserve or avoid wasting natural resources.	SHEDS
Positive attitude to environment	I feel GUILTY when I harm the environment.	SHEDS
Positive attitude to environment	I feel APPRECIATION towards others when they act in an environmentally friendly manner.	SHEDS
Positive attitude to environment	I feel WARM towards others when they conserve or avoid wasting natural resources.	SHEDS
Positive attitude to environment	I feel CONTENT when I act in an environmentally friendly manner.	SHEDS
Positive attitude to environment	I feel INDIGNANT when others act in an environmentally unfriendly manner.	SHEDS
Positive attitude to environment	I feel REGRET when I waste natural resources.	SHEDS

Table A1. *Cont.*

Psychographic Score	Associated Questions (7-Point Likert Scale)	Survey
Positive attitude to environment	I feel ANGRY when others act in an environmentally unfriendly manner.	SHEDS
Positive attitude to environment	I feel ASHAMED when I act in an environmentally unfriendly manner.	SHEDS
Positive attitude to environment	I feel DISGUSTED when others waste natural resources.	SHEDS
Positive attitude to environment	I feel POSITIVE towards others when they act environmentally friendly.	SHEDS
Worried about future of environment	I feel GRATEFUL for our planet and its nature.	SHEDS
Worried about future of environment	I feel WORRIED about the future of our nature.	SHEDS
Worried about future of environment	I feel AWE for our planet and its nature.	SHEDS
Worried about future of environment	I feel ANXIOUS when I think about the future of our planet.	SHEDS
Worried about future of environment	I feel SAD about how mankind treats nature.	SHEDS
Worried about future of environment	I often feel OVERWHELMED by the beauty of nature.	SHEDS
Social expectation to care for environment	I feel morally obliged to support the further development of renewable energies.	Current survey
Social expectation to care for environment	My environment expects me to support the further development of renewable energies.	Current survey
Social expectation to care for environment	The members in my household expect that I behave in an environmentally friendly manner.	SHEDS
Social expectation to care for environment	I believe that most of my acquaintances behave in an environmentally friendly manner whenever it is possible.	SHEDS
Social expectation to care for environment	Most of my acquaintances expect that I behave in an environmentally friendly manner.	SHEDS
Social expectation to care for environment	I feel personally obliged to behave in an environmentally friendly manner as much as possible.	SHEDS
Social expectation to care for environment	In the Swiss society, it is usually expected that one behaves in an environmentally friendly manner.	SHEDS
Maximizer vs. Satisficer	No matter how satisfied I am with my work, it is right for me to look for better options.	Current survey
Maximizer vs. Satisficer	When I am in the car listening to the radio, I often switch to other stations to check if there is something better on, even if I am relatively happy with what I am listening to.	Current survey
Maximizer vs. Satisficer	When I watch TV, I flip through the channels to browse the available options, even while trying to watch a program.	Current survey
Maximizer vs. Satisficer	I treat relationships like clothes: I expect to have to try on a lot before I find the perfect fit.	Current survey
Maximizer vs. Satisficer	I often find it difficult to buy a gift for a friend.	Current survey
1Maximizer vs. Satisficer	Choosing films is really difficult. I always have trouble choosing the best one.	Current survey
Maximizer vs. Satisficer	When shopping, I find it hard to find clothes that I really like.	Current survey
Maximizer vs. Satisficer	I am a big fan of lists that try to put things in order (the best films, the best singers, the best sportsmen, the best novels, etc.).	Current survey
Maximizer vs. Satisficer	I find that writing is very difficult, even if it is just a letter to a friend, because it is so hard to get things right. I often do several drafts even for simple things.	Current survey
Maximizer vs. Satisficer	I never settle for second best.	Current survey
Maximizer vs. Satisficer	Whenever I am faced with a choice, I try to imagine what all the other possibilities are, even those that do not exist at the moment.	Current survey
Maximizer vs. Satisficer	I often dream of living in a way that is different from my actual life.	Current survey
Maximizer vs. Satisficer	No matter what I do, I set the highest standards for myself	Current survey
Political orientation	Below you find a scale that goes from left (1) to right (8). When you think about your own political orientation, how would classify yourself on this scale?	SHEDS

Appendix B

The utility which a respondent cluster attaches to contract is calculated as the sum of average utilities for the respective respondent cluster in Table 6. and the attributes, which are shown in Table A2. For example, contract 3 (TOU, manual) is associated with a utility of

+0.81 (for Cluster 1) and −4.90 (for Cluster 4), which is the sum of average utilities for the “TOU” attribute and the “EMS” attribute for Cluster 1 (+0.81 = −0.7 + 1.51) and Cluster 4 (−4.9 = −2.41 − 2.49). The other attributes of contract 3 correspond to the base-level and do thus not add to the contract utility.

Table A2. Contract attributes and resulting utility of each cluster.

	1. Flat, Manual	**2. TOU, Manual**	**3. TOU, EMS**	**4. TOU, DLC**	**5. TOU, DLC, Guarantee**	**6. Flat, DLC**	**7. Flat, DLC, Guarantee**
Contract attributes							
ASC	0	0	0	0	0	0	0
TOU	0	1	1	1	1	0	0
CPP	0	0	0	0	0	0	0
EMS	0	0	1	0	0	0	0
Utility	0	0	0	1	1	1	1
DUR	0	0	0	0	0	0	0
NLSS	0	0	0	0	0	0	1
GRNT	0	0	0	0	1	0	0
COMP	0	0	0	0	0	0	0
Utility							
Cluster 1	0.00	−0.70	0.81	0.30	1.75	1.00	1.70
Cluster 2	0.00	−3.02	−1.38	−1.39	−0.77	1.63	2.00
Cluster 3	0.00	1.01	0.01	−0.31	0.23	−1.32	−1.14
Cluster 4	0.00	−2.41	−4.90	−4.80	−4.72	−2.39	−2.20

References

1. Bertoldi, P. Policies for energy conservation and sufficiency: Review of existing policies and recommendations for new and effective policies in OECD countries. *Energy Build.* **2022**, *264*, 112075. [CrossRef]
2. BFE. *Studie «Potential Demand Side Management in der Schweiz»*; BET: Zofingen, Switzerland, 2019.
3. Li, P.-H.; Pye, S. Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective. *Appl. Energy* **2018**, *228*, 965–979. [CrossRef]
4. Parrish, B.; Gross, R.; Heptonstall, P. On demand: Can demand response live up to expectations in managing electricity systems? *Energy Res. Soc. Sci.* **2019**, *51*, 107–118. [CrossRef]
5. Harold, J.; Bertsch, V.; Fell, H. *Consumer Preferences for End-Use Specific Curtailable Electricity Contracts on Household Appliances during Peak Load Hours*; ESRI Working Paper No. 632; The Economic and Social Research Institute (ESRI): Dublin, Ireland, 2019.
6. Matisoff, D.C.; Beppler, R.; Chan, G.; Carley, S. A review of barriers in implementing dynamic electricity pricing to achieve cost-causality. *Environ. Res. Lett.* **2020**, *15*, 093006. [CrossRef]
7. Fell, M.J.; Shipworth, D.; Huebner, G.M.; Elwell, C.A. Public acceptability of domestic demand-side response in Great Britain: The role of automation and direct load control. *Energy Res. Soc. Sci.* **2015**, *9*, 72–84. [CrossRef]
8. Eid, C.; Koliou, E.; Valles, M.; Reneses, J.; Hakvoort, R. Time-based pricing and electricity demand response: Existing barriers and next steps. *Util. Policy* **2016**, *40*, 15–25. [CrossRef]
9. Winzer, C.; Ludwig, P. *Optimal Design of Dynamic Grid Tariffs*; SSRN Scholarly Paper 4130379; Social Science Research Network: Rochester, NY, USA, 2022; Available online: https://papers.ssrn.com/abstract=4130379 (accessed on 7 June 2022).
10. Stenner, K.; Frederiks, E.R.; Hobman, E.V.; Cook, S. Willingness to participate in direct load control: The role of consumer distrust. *Appl. Energy* **2017**, *189*, 76–88. [CrossRef]
11. Johnston, R.J.; Boyle, K.J.; Adamowicz, W.; Bennett, J.; Brouwer, R.; Cameron, T.A.; Hanemann, W.M.; Hanley, N.; Ryan, M.; Scarpa, R.; et al. Contemporary Guidance for Stated Preference Studies. *J. Assoc. Environ. Resour. Econ.* **2017**, *4*, 319–405. [CrossRef]
12. Jordehi, A.R. Optimisation of demand response in electric power systems, a review. *Renew. Sustain. Energy Rev.* **2019**, *103*, 308–319. [CrossRef]
13. Parrish, B.; Heptonstall, P.; Gross, R.; Sovacool, B.K. A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. *Energy Policy* **2020**, *138*, 111221. [CrossRef]
14. Faruqui, A.; Sergici, S.; Warner, C. Arcturus 2.0: A meta-analysis of time-varying rates for electricity. *Electr. J.* **2017**, *30*, 64–72. [CrossRef]
15. Faruqui, A.; Sergici, S. Household response to dynamic pricing of electricity: A survey of 15 experiments. *J. Regul. Econ.* **2010**, *38*, 193–225. [CrossRef]
16. Dütschke, E.; Paetz, A.-G. Dynamic electricity pricing—Which programs do consumers prefer? *Energy Policy* **2013**, *59*, 226–234. [CrossRef]
17. Dutta, G.; Mitra, K. A literature review on dynamic pricing of electricity. *J. Oper. Res. Soc.* **2017**, *68*, 1131–1145. [CrossRef]

18. Kessels, K.; Kraan, C.; Karg, L.; Maggiore, S.; Valkering, P.; Laes, E. Fostering Residential Demand Response through Dynamic Pricing Schemes: A Behavioural Review of Smart Grid Pilots in Europe. *Sustainability* **2016**, *8*, 929. [CrossRef]
19. Nicolson, M.; Huebner, G.; Shipworth, D. Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership. *Energy Res. Soc. Sci.* **2017**, *23*, 82–96. [CrossRef]
20. Nicolson, M.L.; Fell, M.J.; Huebner, G.M. Consumer demand for time of use electricity tariffs: A systematized review of the empirical evidence. *Renew. Sustain. Energy Rev.* **2018**, *97*, 276–289. [CrossRef]
21. Stenner, K.; Frederiks, E.; Hobman, E.V.; Meikle, S. *Australian Consumers' Likely Response to Cost-Reflective Electricity Pricing*; CSIRO: Brisbane, Australia, 2015; p. 82.
22. Stromback, J.; Dromacque, C.; Yassin, M.H.; Global Energy Think Tank; Vaasa, E.T.T. The potential of smart meter enabled programs to increase energy and systems efficiency: A mass pilot comparison Short name: Empower Demand. *Vaasa ETT.* 2011. Available online: http://esmig.eu/sites/default/files/empower-demand-report.pdf (accessed on 1 June 2022).
23. Bushnell, J.; Hobbs, B.F.; Wolak, F.A. When It Comes to Demand Response, Is FERC Its Own Worst Enemy? *Electr. J.* **2009**, *22*, 9–18. [CrossRef]
24. Chao, H. Demand response in wholesale electricity markets: The choice of customer baseline. *J. Regul. Econ.* **2011**, *39*, 68–88. [CrossRef]
25. Yilmaz, S.; Xu, X.; Cabrera, D.; Chanez, C.; Cuony, P.; Patel, M.K. Analysis of demand-side response preferences regarding electricity tariffs and direct load control: Key findings from a Swiss survey. *Energy* **2020**, *212*, 118712. [CrossRef]
26. Yilmaz, S.; Cuony, P.; Chanez, C. Prioritize your heat pump or electric vehicle? Analysing design preferences for Direct Load Control programmes in Swiss households. *Energy Res. Soc. Sci.* **2021**, *82*, 102319. [CrossRef]
27. Yilmaz, S.; Chanez, C.; Cuony, P.; Patel, M.K. Analysing utility-based direct load control programmes for heat pumps and electric vehicles considering customer segmentation. *Energy Policy* **2022**, *164*, 112900. [CrossRef]
28. Curtis, J.; Grilli, G.; Brazil, W.; Harold, J. Why do preferences for electricity services differ? Domestic appliance curtailment contracts in Ireland. *Energy Res. Soc. Sci.* **2020**, *69*, 101705. [CrossRef]
29. Sullivan, M.; Schellenberg, J.; Blundell, M. *Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States*; Berkeley Lab: Los Angeles, CA, USA, 2015.
30. Richter, L.-L.; Pollitt, M.G. Which smart electricity service contracts will consumers accept? The demand for compensation in a platform market. *Energy Econ.* **2018**, *72*, 436–450. [CrossRef]
31. Wiekens, C.; Grootel, M.; Steinmeijer, S. *Experiences and Behaviors of End-Users in a Smart Grid: The Influence of Values, Attitudes, Trust, and Several Types of Demand Side Management*; Hanzehogeschool Groningen: Groningen, The Netherlands, 2014.
32. Kubli, M.; Loock, M.; Wüstenhagen, R. The flexible prosumer: Measuring the willingness to co-create distributed flexibility. *Energy Policy* **2018**, *114*, 540–548. [CrossRef]
33. Weber, S.; Burger, P.; Farsi, M.; Martinez-Cruz, A.L.; Puntiroli, M.; Schubert, I.; Volland, B. *Swiss Household Energy Demand Survey (SHEDS): Objectives, Design, and Implementation*; IRENE Working Paper; University of Neuchâtel, Institute of Economic Research (IRENE): Neuchâtel, Switzerland, 2017.
34. Hensher, D.A. Hypothetical bias, choice experiments and willingness to pay. *Transp. Res. Part B Methodol.* **2009**, *44*, 735–752. [CrossRef]
35. Morrissey, K.; Plater, A.; Dean, M. The cost of electric power outages in the residential sector: A willingness to pay approach. *Appl. Energy* **2018**, *212*, 141–150. [CrossRef]
36. Sawtooth Software, Inc. *The CBC System for Choice-Based Conjoint Analysis*; Sawtooth Software, Inc.: Provo, UT, USA, 2017.
37. Reed Johnson, F.; Lancsar, E.; Marshall, D.; Kilambi, V.; Mühlbacher, A.; Regier, D.A.; Bresnahan, B.W.; Kanninen, B.; Bridges, J.F. Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. *Value Health* **2013**, *16*, 3–13. [CrossRef]
38. Train, K. *Discrete Choice Methods With Simulation*; Cambridge University Press: Cambridge, UK, 2009. [CrossRef]
39. Broberg, T.; Persson, L. Is our everyday comfort for sale? Preferences for demand management on the electricity market. *Energy Econ.* **2016**, *54*, 24–32. [CrossRef]
40. Hole, A.R. Fitting Mixed Logit Models by Using Maximum Simulated Likelihood. *Stata J.* **2007**, *7*, 388–401. [CrossRef]
41. Revelt, D.; Train, K. Customer-Specific Taste Parameters and Mixed Logit: Households' Choice of Electricity Supplier. Department of Economics, Institute for Business and Economic Research, UC Berkeley, Department of Economics, Working Paper Series, May 2000. Available online: https://econpapers.repec.org/paper/cdleconwp/qt1900p96t.htm (accessed on 21 April 2021).
42. Bundesamt Für Statistik Schweiz. Population Statistic 2019. Available online: https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung/stand-entwicklung/alter-zivilstand-staatsangehoerigkeit.assetdetail.13707177.html (accessed on 20 April 2021).
43. Bundesamt Für Statistik Schweiz. Housing Conditions 2019. Available online: https://www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/dwellings/housing-conditions.html (accessed on 20 April 2021).
44. Bundesamt Für Statistik Schweiz. Poverty and Living Conditions in 2017. Available online: https://www.bfs.admin.ch/bfs/en/home/statistics/economic-social-situation-population/economic-and-social-situation-of-the-population/inqualities-income-ditribution/income-distribution.assetdetail.8986973.html (accessed on 20 March 2021).
45. Bundesamt Für Statistik Schweiz. Highest Completed Level of Education in 2019. Available online: https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/bildungsstand.assetdetail.15404053.html (accessed on 20 April 2021).

46. Bundesamt Für Statistik Schweiz. Statistics on Energy Agents in Residential Buildings 2017. Available online: https://www.bfs.admin.ch/bfs/en/home/statistics/construction-housing/buildings/energy-field.assetdetail.3982424.html (accessed on 20 April 2021).
47. Swiss Household Energy Demand Survey (SHEDS). Available online: https://www.sccer-crest.ch/research/swiss-household-energy-demand-survey-sheds/ (accessed on 20 April 2021).
48. Wood, Z. Energy Bills: Why Are so Many Smart Meters in Britain Turning 'Dumb'? 2022. Available online: https://www.theguardian.com/money/2022/jun/04/why-are-so-many-smart-meters-turning-dumb-great-britain (accessed on 14 July 2022).