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Consumers' Willingness to Accept Time-of-Use Tariffs for Shifting Electricity Demand

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Abstract: Time-of-use (TOU) electricity tariffs represent an instrument for demand side management. By reducing energy demand during peak times, less investments in otherwise necessary, costly, and CO₂ intensive redispatch would be required. We use a choice experiment (CE) to analyze private consumers' acceptance of TOU tariffs in Germany. In our CE, respondents choose between a fixed rate tariff and two TOU tariffs that differ by peak time scheme and by a control of appliances' electricity consumption during that time. We use a mixed logit model to account for taste heterogeneity. Moreover, investigating decision strategies, we identify three different strategies that shed light on drivers of unobserved taste heterogeneity: (1) Always choosing the status quo, (2) always choosing the maximum discount, and (3) choosing a TOU tariff but not always going for the maximum discount. Overall, about 70% of our 1398 respondents would choose a TOU tariff and shift their electricity demand, leading to a decline in energy demand during peak times. Rough estimates indicate that this would lead to significant savings in electricity generation, avoiding up to a mid to large-sized fossil-fuel power plant.

Keywords: choice experiment; demand-side-management; time-of-use tariff; willingness to accept; mixed logit; energy transition

1. Introduction

Environmental concerns about external effects of conventional electricity generation based on fossil fuels have led to a significant number of regulations on the supply side, fostering e.g., the use of renewable fuels for electricity generation. Regulations on the demand side, in particular demand side management (DSM), are less common. Often DSM aims to encourage consumers to shift electricity demand from peak to off-peak times, such as nighttime and weekends [1]. If the balancing of demand and supply is large enough, it reduces the need for redispatch and ultimately contributes to the mitigation of climate change [2].

Dynamic electricity tariffs incentivize consumers to shift their electricity demand [3]. These tariffs are mainly time-of-use (TOU) tariffs with prices depending on daytime. According to Faruqui and Sergici [4], TOU tariffs could lower the peak demand significantly. They estimate that reductions of 3–6% are achievable. To facilitate the adoption of TOU or more complex tariffs by private households, the EU requires each member state to have at least 80% of consumers equipped with smart meters by 2020 [5]. Empirical evidence on the effectiveness of these measures in shifting demand is rather limited, and the important question remains if consumers would accept such tariffs.

The few studies [6–18] investigating the potential effectiveness of TOU tariffs provide evidence that these tariffs reduce consumers' utility. A drawback of the available studies is, however, that either samples are restricted to certain consumer groups or sample sizes are too low to derive general conclusions. Exceptions are Goett et al. [8] and Broberg and Persson [12].

From a country's perspective, Germany is particularly interesting, since the ongoing energy transition requires substantial investments, such as redispatch and network expansion, to keep up with the current demand fluctuations [19]. So far, only Dütschke and Paetz [17] and Schlereth et al. [18] provided information on consumers' preferences for dynamic electricity tariffs including TOU tariffs. Dütschke and Paetz [17], however, use a non-representative, small sample for their analysis, and Schlereth et al. [18] focus on respondents' risk attitudes.

We address this knowledge gap by using a choice experiment (CE) to analyze acceptance of TOU tariffs in Germany. Our study contributes to the current literature as follows: First, using a large sample of about 1400 respondents, we estimate respondents' overall willingness to accept (WTA) these tariffs, depending on the peak times and a control of appliances' electricity consumption. To our knowledge, this is the first study to account for separate appliances. Second, we identify the following three decision strategies used by respondents: (1) Always choosing the status quo, (2) always choosing the maximum discount, and (3) choosing a TOU tariff but not always going for the maximum discount. Finally, we show that about 70% of our respondents would choose a TOU tariff and shift their electricity demand of which about 50% would accept a control of appliances' electricity consumption during peak times. Thus, TOU tariffs could enable significant demand shifting during peak times in Germany.

Our paper proceeds as follows: Section 2 provides an overview of former experiments on consumers' preferences for TOU tariffs. Section 3 explains our CE and our estimation method. Section 4 presents our results, i.e., our WTA estimates including an analysis of their heterogeneity followed by a discussion of WTA for a control of certain appliances. Section 5 contains a scenario analysis estimating the potential effect of appliance control on electricity demand during peak times based on our CE results. Section 6 concludes and discusses our results.

2. Literature Review

Information on consumers' acceptance of TOU tariffs is limited. Nicolson et al. [7] found in their meta-analysis covering 27 studies (66 measures) a consensus in the literature that TOU tariffs are less preferred than fixed rate tariffs. While Nicolsen et al. [6] found that 39% of their British respondents state that they are willing to switch to a "smart" TOU tariff.

In the following, we discuss the present studies in a chronological order but will turn to studies using data from Germany at the end of the review. Focusing on the United States, Goett et al. [8] conducted a series of CEs to gain insight into costumers' preferences for more than 40 tariff attributes. To reduce costumers' cognitive burden, they defined five clusters of attributes. Overall, they presented four choice sets of each cluster of attributes to the customers. One of those clusters contained, besides general service attributes, variable electricity rates, i.e., seasonal rates, time of day rates, and hourly rates. Based on data from 1205 interviews in a phone-mail-phone format they found that fixed rates are preferred over seasonal rates; seasonal rates are preferred over time of day rates; and time of day rates are preferred over hourly rates.

Using a much smaller sample, Kaufmann et al. [9] compared different critical peak price (CPP) tariffs using a web-based CE. Their sample consists of 87 customers of a Swiss utility company. They found that consumers prefer CPP tariffs with low-price differences to those with high price differences. More generally, the CE by Buryk et al. [10] investigates which kind of electricity tariff—fixed rate, TOU tariff, or CPP tariff—provides the highest utility for consumers in the EU and the United States. They distributed their online survey, which comprised 160 usable interviews, through social media. They notice that fixed rate tariffs are always preferred to dynamic tariffs (and TOU tariffs are preferred to CPP tariffs). Furthermore, consumers' acceptance of dynamic tariffs increases if they are previously

informed about positive side effects of dynamic tariffs. These findings are in line with the results by Hall et al. [11] who conducted a non-representative opinion survey in Australia.

Focusing on the innovative tariff characteristics, Broberg and Persson [12] analyzed in their CE consumers' WTA for dynamic tariffs allowing for external control of heating and electricity consumption during peak times. Their sample of 918 web-panel participants is representative for Sweden. The study's findings confirm consumers' aversion to adapting their behavior to dynamic electricity tariffs, and to a control of heating and electricity consumption. Using this data set, Daniel et al. [13] used an elimination-by-aspects model for estimating consumers' WTA for TOU tariffs and find that respondents indeed eliminate certain aspects (e.g., a restriction of their electricity consumption) in their decision-making process.

More recently, Richter and Politt [14] used a CE to gain insight into consumers' preferences for additional demand response measures in electricity contracts in Great Britain. They focused on smart energy services such as technical support and control of electricity usage. Based on an online survey with a sample of 1892 respondents, they found that respondents are willing to pay for technical support but require a compensation for the control of their electricity usage.

Finally, Ruokamo et al. [15] combined in a CE dynamic tariffs with information on CO₂-emission reductions. Their online-survey is based on responses of about 380 Finnish homeowners. Respondents could choose between real-time pricing, two-rate, and power-based tariffs. The tariffs further varied in terms of CO₂-emission reductions and load control (electricity and/or heating) from either 7 to 10 am or from 5 to 8 pm. Overall, they confirm previous findings regarding preferences for dynamic electricity tariffs but environmental benefits would increase utility. Interestingly, respondents would rather accept a restriction of their heating than on their electricity consumption.

Turning to studies from Germany, Stamminger and Anstett [16] conducted a small field experiment to investigate if consumers are able and willing to adjust their residential energy consumption to varying prices. In their hypothetical TOU tariff electricity prices varied between 10 and 40 €/kWh. They equipped all 67 participants with intelligent smart meters but only 41 of them also with smart appliances (washing machine and dryer). Over the project time of two years, consumers were able to save on average 25% of their electricity costs compared to a fixed rate tariff (25 €/kWh) by shifting their electricity demand to times with high renewable energy supply. However, because of their experimental design, the sample only includes consumers with a general interest in dynamic electricity tariffs and smart appliances.

Dütschke and Paetz [17] used two small, non-representative experiments: an online CE ($N = 160$) and a field study with smart-home owners ($N = 4$), to investigate respondents' preferences for dynamic electricity tariffs. Unlike findings in other countries, automated demand response, i.e., an automated control of electricity usage, is preferred over manual demand response.

More recently, Schlereth et al. [18] conducted an online CE with 779 customers of one electricity provider. Their CE aimed at measuring consumers' acceptance of different dynamic pricing schemes. The pricing schemes included information about the expected rise in the electricity bill if electricity consumption is not adjusted to rising prices; and information about the expected reduction in the electricity bill if electricity consumption is adjusted. They found that a substantial decrease in consumers' electricity bill would be necessary to significantly increase their acceptance of dynamic electricity tariffs.

Summing up, TOU tariffs decrease consumers' utility requiring monetary compensation for acceptance but studies found ambiguous results regarding consumers' acceptance of appliance control [12,16]. However, it has not yet been investigated if consumers' acceptance changes with varying peak times, or if consumers' acceptance of appliance control actually depends on the type of appliance. Gaining insights into consumers' acceptance of appliance control enables decision-makers to promote this measure, and thus, to shift electricity demand to off-peak times.

Given these knowledge gaps, our study focuses on the following four research questions. First, we analyze if different peak times (time schemes with high prices, e.g., only 6–10 am) affect consumer's

acceptance of TOU tariffs. Second, we include different appliances that a respondent's utility company may control individually (Broberg and Persson [12] include a control of heating and electricity appliances without separating between them) during peak times. Consumers might, for example, be more willing to accept a control of their washing machine than of their freezer. Third, we analyze if consumers show dominant decision-making behavior, i.e., decision strategies, by analyzing individual WTA values using individual-level parameter estimates as for example performed by Greene et al. [20] or Franceschinis et al. [21]. We expect, for example, to identify respondents who will never choose a TOU tariff, regardless of a discount, because of their perceived discomfort. Finally, we focus on Germany, a country where the ongoing energy transition requires substantial investments, such as redispatch and network expansion, to keep up with current demand fluctuation. We use our results for a scenario analysis to show that controlling appliances' electricity consumption may potentially lead to a significant shift in electricity demand during peak times, and therefore, to less need for redispatch.

3. Methodology and Data

3.1. Design of the Choice Experiment

Previous research found evidence that peak time pricing decreases consumers' utility (e.g., [10]). We build on this evidence and differentiate between the days at which peak time pricing occurs and the time of the day. First, distinguishing between weekdays and weekends, we hypothesize that consumers' willingness to shift electricity demand on weekends when most people are not working and are more flexible in their use of time exceeds that for weekdays. The compensation for peak time pricing on weekends compared to peak time pricing on weekdays should on average be lower. Second, we distinguish between two peak time pricing schemes. We designed a scheme with typical peak times, such as in the morning or in the evening. These are the hours when households' and overall electricity consumption is high: between 6 am and 10 am and between 4 pm and 8 pm. Next, to acknowledge a certain level of supply uncertainty, we designed a scheme with peak time pricing at four consecutive hours without specifying the exact take-off hour. We hypothesize that consumers' WTA varies over the different time schemes.

Utility companies could incentivize consumers' choice for TOU tariffs by offering additional services through smart meter technologies, such as allowing for external control of appliances. Controlling appliances during peak times to shift electricity consumption to off-peak times—similar to DSM in the industrial sector—could have several positive effects including monetary savings for consumers. We offer control separately for individual appliances and inform respondents that their utility company would control these. In our CE, the following appliances are considered: a household's washing machine, dryer, dishwasher, and freezer. Further, we use a discount on consumers' electricity bill (compare Table 1), as the price attribute to calculate the necessary compensational payment for consumers to accept TOU tariffs. Utility companies would pay this discount until consumers choose another electricity tariff.

These considerations led to our CE in which respondents faced three alternatives, two tariffs with dynamic electricity prices, i.e., TOU tariffs (we are aware that real time pricing tariffs would reflect the situation in the electricity market more accurately but these tariffs are, however, still uncommon in Germany, i.e., they are only available in pilot projects), and one with a fixed electricity price (status quo). Our status quo tariff exhibits the usual characteristics of an electricity tariff in Germany, i.e., a fixed rate tariff with a fixed electricity price amounting to the average electricity price in 2016 in Germany. As shown in Table 1, each tariff has seven attributes: (1) Peak time on weekdays (Monday to Friday); (2) peak time on weekends (Saturday and Sunday); option to allow the electricity provider to control the electricity consumption of appliances during peak times, including (3) washing machine, (4) dryer, (5) dishwasher, and (6) freezer; and (7) amount of monthly electricity discount. Additionally, Table 1 provides an overview on attributes' levels.

We are aware that more general electricity tariff characteristics, e.g., contract length, payment standards, and utility company, affect consumers' decisions of choosing an electricity tariff [8]. Therefore, we explicitly remind the survey participants that all other tariff characteristics are identical for those three tariffs (e.g., utility company, payment method, cancellation period, base fee), and that they solely can choose between tariffs being presented to them.

Table 1. Attributes, their description, and their levels.

Attribute	Description	Levels ¹
Peak time (PT)—Depending on the day of the week	With PT pricing, electricity prices are either variable on <i>Monday to Friday, and Saturday and Sunday</i> or only <i>Monday to Friday</i> (with a fixed electricity price of 29 ct/kWh on Saturdays and Sundays). On these days, for <i>four hours a day</i> PT electricity price is 40 ct/kWh. The off-peak time electricity price is 10 ct/kWh. PT occurs Monday to Friday, respectively Saturday and Sunday, either <i>during the same time of the day</i> or <i>during daily changing times</i> (4 h/day between 6 am and 8 pm) of which your electricity supplier informs you one day in advance.	Peak time on weekdays: <i>No peak time pricing</i> , 4 h/day (consecutive between 6 am and 8 pm), 6–10 am, 4–8 pm, 6–8 am and 6–8 pm Peak time on weekends: <i>No peak time pricing</i> , 4 h/day (consecutive between 6 am and 8 pm), 6–10 am, 4–8 pm
Controlling appliances' electricity consumption during peak times	<i>During PT</i> , your electricity supplier <i>controls electricity consumption</i> of the following appliances: washing machine, dryer, dishwasher ² , and/or freezer ³ , so that these appliances consume less electricity at times of high prices.	By appliance (washing machine, dryer, dishwasher, freezer): <u>No</u> , Yes
Monthly discount on electricity bill	In a dynamic electricity tariff, you receive a fixed monthly discount on your electricity bill.	Discount: <u>0€</u> , 5€, 10€, 15€, 20€

Note: ¹ Levels in italics are only those of the status quo (€0 discount and no peak time). Underlined levels are those of the status quo and partly of TOU tariffs (no control of appliances and no peak time on weekends). ² We informed respondents that a control of electricity consumption of their washing machine, dryer, and/or dishwasher means that a program will not start during peak times but after that period. If appliances are already running when peak time starts, the program will continue and not being paused. ³ We informed respondents that their freezer's electricity consumption would only be paused in case of critical situations, i.e., in case of an emergency to avoid an electrical power outage.

3.2. Questionnaire and Choice Set Design

In the questionnaire, we first briefly introduced our survey topic and asked a few screen-out questions to ensure an approximate representativeness of the German population regarding age, gender, and region. Second, we continued with some warm-up questions about a households' electricity consumption, their current electricity tariff, and their home's equipment with electric heating, and private microgeneration, e.g., solar panels.

Then, we introduced our CE. First, we briefly explained why smart meters are necessary for offering complex TOU tariffs and asked for respondent's acceptance of smart meters. Second, we explained DSM's purpose in balancing electricity supply and demand through TOU tariffs. The Appendix A provides an English translation of this informational text. Third, we introduced the CE by describing a tariff's attributes and their levels (see Table 1). Then, we presented eight choice sets to each respondent. Note that we used an orthogonal fractional factorial design with 64 choice sets. Out of these, we randomly assigned eight sets to each respondent. Figure 1 presents a translated example of a choice set.

The fourth part consisted of debriefing questions. For instance, we asked respondents which of the appliances, included in our CE as attributes (washer, dryer, dishwasher, freezer), their household owns, and for the time of day respondents usually consume much electricity. To test if respondents share specific decision strategies, we asked them to describe their decision-making procedure in the CE using an open-ended text field. Finally, the common sociodemographic characteristics were requested. As usual, we used a pilot study with 102 respondents to review our questionnaire.

Please have a close look at the electricity tariffs below.

Which one of these electricity tariffs would you choose?

Type of electricity tariff:		Tariff 1	Tariff 2	Tariff 3
		Varying electricity prices	Varying electricity prices	Fixed electricity price
Peak time:	Monday to Friday:	4 h/day	6–8 am and 6–8 pm	None
	Saturday and Sunday:	4 h/day	6–10 am	None
Control:	Washer:	Yes	No	No
	Dryer:	No	Yes	No
	Dishwasher:	No	No	No
	Freezer:	Yes	Yes	No
Monthly discount:		5€	20€	0€

I choose:

- Tariff 1
- Tariff 2
- Tariff 3

Figure 1. Translated choice set. Tariff 3 was introduced as status quo.

3.3. Econometric Approach

In a CE, one assumes that the utility of an object is the sum of its attributes' utility, and that decision-making is in line with random utility theory [22]. Thus, when facing choice set C , individual n chooses alternative j if and only if individual n obtains maximum utility by choosing alternative j . Additionally, one decomposes individual n 's utility U_{nj} obtained by alternative j into a direct, observable utility V_{nj} , which covers utility obtained by object's attributes, and an indirect, unobservable utility ε_{nj} , which is distributed Type I extreme value.

As a first step, we use a conditional logit (CL) specification [22] to estimate the vector of fixed marginal utilities β' of the K attributes of our electricity tariffs conditional on the choice set C . We assume a linear direct utility function: $V_{nj} = \beta'x_{nj}$, with x_{nj} is a vector of observed attribute levels by individual n in alternative j . Therefore, the probability of individual n choosing electricity tariff i when facing choice set C is given by:

$$P_{ni} = \frac{\exp(\beta'x_{ni})}{\sum_{j \in C} \exp(\beta'x_{nj})} \quad (1)$$

To account for taste heterogeneity and the panel structure of the data [23], we extend our first model by defining the utility that individual n obtains by choosing electricity tariff j in choice situation t as: $U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt}$. At this juncture, β_n is a vector of individual-specific marginal utilities, x_{njt} is a vector of attribute levels, which individual n observes for electricity tariff j in choice situation t , and ε_{njt} , again, is a random term following a type I extreme value distribution. Similar to Equation (1) the probability of individual n choosing electricity tariff j in choice situation t conditional on knowing β_n is given by

$$L_{njt}(\beta_n) = \frac{\exp(\beta'_n x_{njt})}{\sum_{j \in J} \exp(\beta'_n x_{njt})}. \quad (2)$$

We estimate these unconditional marginal utilities using the Stata add-on "mixlogit" by Hole [24]. This add-on approximates the true log likelihood function, which has no analytical form, by simulation (see e.g., [24,25] for a more detailed description).

Additionally, we analyze respondents' individual marginal utility, respectively respondents' individual-level-parameters (ILP). By estimating the mixed logit (MXL) model, we obtain an unconditional distribution of β in the population. Using the unconditional distribution and Bayes' rule,

we simulate the conditional distribution of β_n to estimate the ILP (see [25] for a detailed mathematical representation).

Practically, we need to make assumptions about the statistical distribution of those marginal utilities, i.e., attributes, and we need to set the number of Halton draws used during the simulation process to estimate the MXL model. We want to allow attributes' marginal utility to embrace positive and negative values; hence, we assume that attributes' marginal utility follow a normal distribution, but discount's marginal utility. An increasing discount usually increases utility, i.e., marginal utility embraces only positive values; hence, we assume that it follows a log normal distribution, which is restricted to positive values. Further, our simulation uses 1000 Halton draws.

Finally, we use the conditional and the unconditional marginal utilities to estimate the respective WTA for the different attributes of the TOU tariffs. The WTA for a level change in an attribute, in reference to the status quo option, is the marginal rate of substitution between the marginal utility β_k obtained by attribute k and the marginal utility $\beta_{discount}$ by a change in the discount:

$$WTA_k = -\frac{\beta_k}{\beta_{discount}} \quad (3)$$

As suggested by Bliemer and Rose [26], we use the median of the parameter estimates instead of their mean to calculate the marginal WTA. Further, we use Stata's "nlcom" command, which uses the delta method to estimate the standard errors. Note that we calculated the median ILP of the discount as: $median\beta_{discount} = exp(\beta_{ln\ discount})$. Note that: (1) In a CL median WTA equals mean WTA, because the quotient of a normal distributed variable and a constant is itself normal distributed, i.e., its median equals its mean. (2) We do not need to correct the sign of the discount coefficient, since it is by definition already positive.

3.4. Identifying Decision Strategies across Respondent Groups

Daniel et al. [13] showed that consumers indeed use simplifying decision strategies when selecting TOU tariffs in a CE. Thus, we hypothesize to find those strategies as well. In contrast to Daniel et al. [13], who used an elimination-by aspects-model, we use respondents' ILP estimates from the MXL model to investigate simplifying decision strategies. Since WTA is the marginal rate of substitution between attribute coefficient and price coefficient, systematic differences in the marginal utility of discount resulting from strategic behavior, for example, might systematically lead to differences in WTA estimates. We identify those differences using a kernel density estimation of respondents' ILPs from our MXL model output, which illustrates their statistical distribution. If this distribution exhibits multiple local maxima, instead of only one global maximum, those estimates are not from the same distribution. Thus, the way respondents react to offered discounts, e.g., following always the same pattern would be an additional cause of variance in WTA estimates.

4. Results

4.1. Descriptive Results

Respondents aged between 18 and 70 were drawn from an online panel supplied by an international panel provider. This sample is not probability-based but, due to using quotas, it is very similar to the German population regarding gender, age, and federal state. The survey took place in January and February 2017. Table 2 reports the socio-demographic characteristics of our final sample of 1398 respondents. We have slightly more females than males in our sample. Further, people aged between 40 and 49 are overrepresented while elderly, aged between 60 and 70, are underrepresented. As usual in online surveys, low educated people are underrepresented.

Table 2. Descriptive statistics.

Characteristics	Values	Sample (N = 1398)	Germany ¹
Gender	Female	50.86%	49.56%
	Male	49.14%	50.44%
Age	18–29 years	20.96%	20.36%
	30–39 years	17.45%	18.33%
	40–49 years	23.18%	18.81%
	50–59 years	22.03%	23.44%
	60–70 years	16.38%	19.06%
	Mean		44.25 years
Highest level of education ²	5 years of secondary education	10.31%	22.28%
	6 years of secondary education	31.87%	32.37%
	8–9 years of secondary education	25.96%	17.47%
	Bachelor degree	8.80%	2.82%
	Master degree (or equivalent)	15.43%	14.91%
	PhD	0.94%	1.15%
	Other	6.70%	9.01%

Note: ¹ Own calculations based on [27,28] for 2017. ² For Germany: This includes population aged 15–65.

Table 3 provides an overview of respondents’ appliance ownership and the times of high electricity consumption of their household differentiating between weekdays and weekends as well as different daytimes. We notice that controlling washing machines’ electricity consumption potentially affects almost all respondents, about three-quarter of the households own a dishwasher and/or a freezer but only less than half of the households own a dryer.

Table 3. Appliance ownership/times of high electricity consumption.

Question:		Share of Respondents Answering “Yes” ²	
Which of the following appliances are available in your household?	Washing machine:	95.85%	
	Dryer:	45.35%	
	Dishwasher:	74.89%	
	Freezer:	80.33%	
	None of these:	1.50%	
When does your household usually consume comparatively much electricity? ¹	Weekdays	6 am–8 pm	93.63%
		6–10 am	23.25%
		4–8 pm	63.02%
		6–8 am/pm	56.87%
	Weekends	6 am–8 pm	91.20%
		6–10 am	17.53%
		4–8 pm	51.79%

Note: ¹ Respondents were asked if they consume much electricity using two-hour intervals, e.g., 6–8 am, 8–10 am.

² Multiple choices possible.

Further, respondents should state their times of “relatively high” electricity consumption. Half of our respondents indicate that their electricity consumption is higher in the afternoon (4–8 pm), but less than a quarter of them state high consumption levels in the morning (6–10 am). As a consequence, the WTA peak time pricing in the morning might be lower than in the evening.

4.2. Estimation Results

Table 4 provides an overview of the estimated marginal utilities by electricity tariff attribute and model; both, for the CL and the MXL model specifications (see Section 3.3). In general, both models

suggest similar effects on utility. However, in terms of the results of the log likelihood function and McFadden pseudo- R^2 the MXL model significantly outperforms the CL model. Additionally, the estimated standard deviations of the random coefficients in the MXL model are highly significant. Thus, we indeed find significant unobserved taste heterogeneity between respondents.

Table 4. Estimation of choice experiment.

Attribute	Conditional Logit (CL)		Mixed Logit (MXL)			
	Coefficient	z-Statistic	Mean	z-Statistic	Std. Deviation	z-Statistic
Mon-Fry: 4 h/day	-0.8688 *** (0.0601)	-14.46	-1.236 *** (0.000)	-10.85	1.336 *** (0.000)	10.05
Mon-Fry: 6–10 am	-0.7287 *** (0.0599)	-12.18	-0.9603 *** (0.000)	-8.34	1.480 *** (0.000)	12.12
Mon-Fry: 4–8 pm	-0.8686 *** (0.0607)	-14.32	-1.211 *** (0.000)	-10.20	1.516 *** (0.000)	11.75
Mon-Fry: 6–8 am/pm	-0.7662 *** (0.0608)	-12.60	-0.9950 *** (0.000)	-8.43	1.430 *** (0.000)	10.64
Sat/Sun: 4 h/day	-0.0258 (0.0408)	-0.63	-0.1659 * (0.054)	-1.93	0.9833 *** (0.000)	6.68
Sat/Sun: 6–10 am	-0.0050 (0.0404)	-0.12	-0.0869 (0.320)	-1.00	0.9390 *** (0.000)	5.58
Sat/Sun: 4–8 pm	-0.0613 (0.0406)	-1.51	-0.2301 ** (0.011)	-2.55	1.290 *** (0.000)	9.57
Washing machine	0.2346 *** (0.0288)	8.14	0.2299 *** (0.005)	2.83	1.939 *** (0.000)	17.39
Dryer	0.0204 (0.0288)	0.71	-0.1431 * (0.057)	-1.90	1.561 *** (0.000)	15.84
Dishwasher	0.1309 *** (0.0284)	4.60	0.0526 (0.466)	0.73	1.574 *** (0.000)	16.13
Freezer	0.0772 *** (0.0284)	2.71	-0.2086 *** (0.010)	-2.59	1.997 *** (0.000)	19.60
Discount	0.0442 *** (0.0026)	-17.02	0.4182 *** (0.000)	-23.20	2.160 *** (0.000)	17.07
Log Likelihood	-12,060.763				-9247.2495	
Log Likelihood null model	-12,267.012				-12,267.012	
McFadden Pseudo R^2	0.02				0.25	

Note: ***: Significance at the 1% level; **: Significance at the 5% level; *: Significance at the 10% level. Estimation is based on 11,184 observations. Standard errors are in brackets. Attributes except for discount are dummy coded. Baseline: Status quo, i.e., fixed rate tariff without control of appliances.

Independent of the model specification, the attributes *discount*, *peak times on weekdays*, and controlling *washing machine's* electricity consumption are significant at the 1%-level. This indicates that those attributes are important drivers of (dis)utility with *peak times on weekdays* showing the largest negative effect size. As expected, a higher *discount* increases utility. Note that we did not find significant differences in the coefficients for the attribute levels *Mon-Fry: 4 h/day* and *Mon-Fry: 4–8 pm* as well as in the coefficients *Mon-Fry: 6–10 am* and *Mon-Fry: 6–8 am/pm*. Therefore, we can only draw the conclusion here that consumers distinguish between certain peak times. The positive effect of controlling the electricity consumption of the washing machine is small but significant. For all other attributes, we find ambiguous results for both model specifications regarding significance and effect direction.

Before discussing the heterogeneity in WTA estimates, we present the estimated unconditional marginal WTA based on our preferred MXL specification (Table 5). Obviously, utility companies have to compensate consumers for accepting TOU tariffs. The estimated marginal WTA for peak time pricing on weekdays varies between 23.67 € and 30.46 € per household and month. Respondents' marginal WTA is lower for peak time pricing in the morning and higher for peak time pricing in the evening. This is not surprising as only 23% of the respondents state that they consume much electricity between 6 and 10 am on weekdays, whereas 63% consume much electricity between 4 and 8 pm on weekdays (see Table 3). Finally, WTA is highest if the peak time during the week is not further specified (four consecutive hours between 6 am and 8 pm). Comparing the results for weekdays and weekends,

marginal WTA for peak time pricing on weekends is on average much lower. Like peak time pricing on weekdays, however, marginal WTA for peak time pricing in the evening exceeds peak time pricing in the morning, which is statistically not different from zero.

Table 5. Unconditional WTA in € based on MXL results.

Attribute	Marginal WTA ¹	Unconditional WTA		
		Standard Error	p-Value	95% Confidence Interval
Mon-Fry: 4 h/day	30.46 ***	4.22	0.000	[22.19, 38.73]
Mon-Fry: 6–10 am	23.67 ***	3.57	0.000	[16.67, 30.67]
Mon-Fry: 4–8 pm	29.86 ***	4.16	0.000	[21.70, 38.02]
Mon-Fry: 6–8 am/pm	24.53 ***	3.67	0.000	[17.33, 31.72]
Sat/Sun: 4 h/day	4.09 *	2.19	0.062	[−0.21, 8.39]
Sat/Sun: 6–10 am	2.14	2.17	0.324	[−2.11, 6.40]
Sat/Sun: 4–8 pm	5.67 **	2.33	0.015	[1.10, 10.25]
Washing machine	−5.67 ***	2.15	0.008	[−9.87, −1.46]
Dryer	3.53 *	1.93	0.068	[−0.26, 7.32]
Dishwasher	−1.30	1.79	0.469	[−4.80, 2.21]
Freezer	5.14 **	2.11	0.015	[1.01, 9.28]

Note: ***: Significance at the 1% level; **: Significance at the 5% level; *: Significance at the 10% level. Attributes except discount are dummy coded. Baseline: Status quo, i.e., fixed rate tariff without control. ¹ We used the median of the discount coefficient (0.041) for estimating marginal WTA.

Furthermore, we find that preferences for a control of electricity consumption during peak times differ across appliances. Respondents require a lower overall compensation (WTA is negative) for accepting a control of their washing machine, no compensation for the control of their dishwasher (insignificant) but an additional compensation for the control of their freezer or dryer (WTA is positive). In general, studies outside of Germany (e.g., [12,15]) found that consumers dislike a control of their electricity consumption but these studies do not differentiate between appliances. For Germany, Dütchke and Paetz [17] discovered that households prefer an automated electricity control over a manual one.

4.3. Decision Strategies across Respondent Groups

To identify individual decision strategies, we additionally investigate the individual-level discount parameters by performing a kernel density estimation. This density function has a kinked maximum close to zero (i.e., respondents who respond weakly to discounts) and fat tails on the right-hand side with a local maximum at very high parameter values (i.e., respondents who respond strongly to discounts).

We find that decision strategies induce local maxima significantly affecting the variance in the kernel density estimation. To be precise, respondents' responses to price changes and their (dis-)like of TOU tariffs strongly affect their discount parameters. If we successively exclude respondent groups by their strategy, we find that the discount parameters significantly differ by decision strategy. Excluding respondents always choosing the maximum discount (strong price reaction) we discover that they exhibit discount parameter values larger than one. Next, excluding those always choosing a fixed rate tariff (no price response at all) their discount parameters are smaller than 0.3.

Overall, this procedure results in four mutual exclusive respondent groups based on respondents' stated choices: (1) A group revealing no dominant decision strategy (34.05%); (2) a group always choosing a fixed rate tariff, i.e., the status quo option (20.31%); (3) a group always choosing the maximum discount option (9.44%); and (4) a group always choosing a TOU tariff, but not necessarily the maximum discount (36.19%). Comparing these four groups in terms of their socio-demographic characteristics reveals that these characteristics are not sufficient to explain the decision strategies (additionally, we conducted a latent class analysis that resulted in a four-class-model. The groups differed by the same factors identified in the MXL model, i.e., how often respondents chose the

status quo and how often they chose the maximum discount. Like in our analysis of individual level parameters, the main driver of class membership is respondent's general (dis-)like of TOU tariffs and their preferences for a monetary compensation; it is not determined by the respondent's sociodemographic characteristics. We provide those results upon request). This is in line with previous results (e.g., [13]).

In the following, we investigate how the decision strategies of these four respondent groups affect the WTA estimates. We, again, use kernel density estimations, but now by respondent group. Figure 2 illustrates these kernel density estimates in four separate figures with individual scale dimensions for densities and marginal utility of discount because of remarkable differences in parameter size.

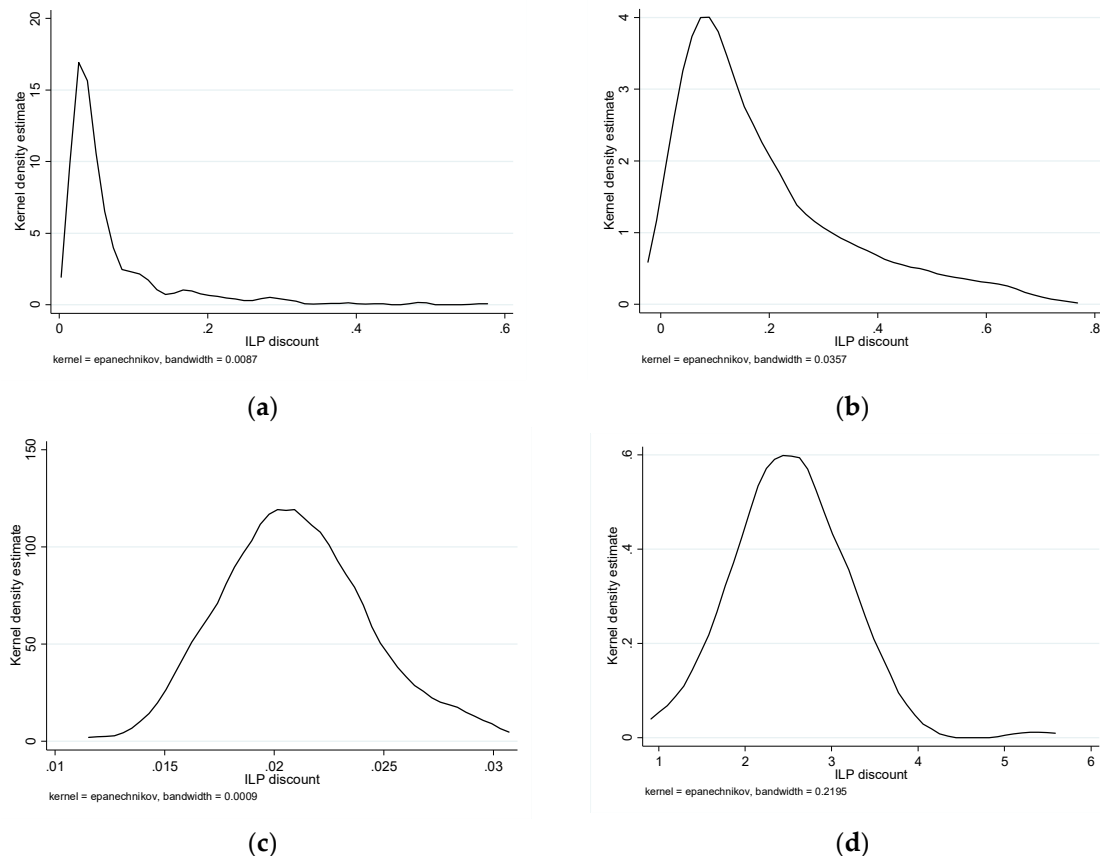


Figure 2. Kernel density estimates of individual-level discount parameters by respondent group. (a) Respondents without dominant strategy; (b) respondents who never chose the status quo but not always the maximum discount; (c) respondents who always chose the status quo; (d) Respondents who always chose the maximum discount.

Visual inspection of Figure 2a–d and pairwise two-sample Kolmogorov-Smirnov tests on equal distributions (each group against each other groups) clearly suggest that discount parameters' distribution significantly differ by respondent group. These findings match respondents' decision strategies. Respondents with a small marginal utility of discount elicit higher WTA values compared to respondents with a high marginal utility of discount (the marginal utility of discount denotes the denominator of the ratio defining WTA, i.e., the marginal rate of substitution).

To clarify this relationship between individual discount parameter estimates and WTA, we calculate the marginal conditional WTA for our sample and by respondent group (see Table 6). For the sample as a whole, the marginal conditional WTA is about half the size of the marginal unconditional WTA (compare Table 5). They differ because, as showed in Section 3.3, marginal unconditional WTA corresponds to the sample's WTA distribution, whereas marginal conditional WTA corresponds to respondents' individual WTA distribution, based on their individual-level-parameters.

Table 6. Median of marginal conditional WTA in € (in brackets: [5%-quantile, 95%-quantile]).

	Sample	No Dominant Strategy	Never Chose the Status Quo	Always Chose the Max. Discount	Always Chose the Status Quo
	N = 1398 (100%)	N = 476 (34.05%)	N = 506 (36.19%)	N = 132 (9.44%)	N = 284 (20.31%)
Mon-Fry:	14.46	24.97	6.30	0.48	81.66
4 h/day	[0.03, 105.05]	[-2.48, 93.95]	[-1.72, 36.93]	[0.26, 0.92]	[58.35, 123.27]
Mon-Fry:	9.52	17.20	3.73	0.36	74.26
6–10 am	[-6.43, 92.98]	[-12.89, 92.98]	[-7.18, 31.34]	[0.13, 0.82]	[48.92, 104.84]
Mon-Fry:	14.44	27.28	4.76	0.49	84.53
4–8 pm	[-2.10, 103.96]	[-6.96, 107.46]	[-3.31, 30.98]	[0.19, 0.97]	[61.64, 116.18]
Mon-Fry:	12.23	21.09	4.23	0.36	72.02
6–8 am/pm	[-3.51, 88.79]	[-4.95, 85.32]	[-6.18, 33.82]	[0.05, 0.79]	[47.22, 107.68]
Sat/Sun:	2.03	3.97	0.30	0.04	19.03
4 h/day	[-10.42, 28.82]	[-14.55, 30.96]	[-9.73, 33.82]	[-0.11, 0.20]	[7.12, 31.99]
Sat/Sun:	0.92	1.66	-0.14	0.04	15.09
6–10 am	[-10.57, 22.51]	[-16.12, 25.76]	[-10.54, 6.69]	[-0.11, 0.19]	[6.23, 25.89]
Sat/Sun:	2.68	5.31	-0.16	0.09	26.76
4–8 pm	[-14.98, 42.50]	[-25.77, 44.29]	[-15.38, 12.69]	[-0.18, 0.40]	[10.42, 50.58]
Washing machine	-0.31	-2.77	-7.22	-0.13	55.75
	[-50.77, 72.73]	[-70.05, 58.58]	[-50.26, 4.05]	[-0.71, 0.38]	[30.09, 85.20]
Dryer	0.56	4.24	-2.40	0.00	53.13
	[-28.22, 65.76]	[-34.82, 59.48]	[-32.28, 5.87]	[-0.38, 0.36]	[32.23, 77.70]
Dishwasher	0.02	-0.09	-4.09	-0.05	46.68
	[-35.75, 58.14]	[-46.21, 50.08]	[-40.28, 6.40]	[-0.54, 0.34]	[23.98, 70.21]
Freezer	0.49	5.35	-4.71	-0.04	76.03
	[-35.51, 91.79]	[-48.76, 81.12]	[-40.11, 10.08]	[-0.67, 0.50]	[50.60, 110.30]

Note: Attributes except discount are dummy coded. Baseline: Status quo, i.e., fixed rate tariff without controlling.

Comparing marginal conditional WTA values by respondent group (Table 6), results are in line with the kernel density estimations by respondent group. On the one hand, we elicit meaningful WTA values for those 70% of our respondents who neither always chose the maximum discount nor always chose a fixed rate tariff (panels (a) and (b) in Figure 2). These respondents are potential purchasers of TOU tariffs. On the other hand, we elicit WTA values for the remaining 30% of our sample that are either very high or not significantly different from zero. We identify those respondents as potential non-purchasers of TOU tariffs.

Focusing on the two groups of potential TOU tariff purchasers first, marginal WTA of respondents without dominant decision strategies is significantly higher for peak times on weekdays (Table 6) compared to those respondents who always choose a TOU tariff (panels (a) and (b) in Figure 2). This is because the latter group has a significantly lower marginal utility of discount. Further, absolute marginal WTA of potential purchasers for peak times on weekends is significantly lower than for peak times on weekdays. Interestingly, the 5%-quantile of WTA is even negative for all peak times for both groups, i.e., some potential purchasers would not even require a compensation when purchasing a TOU tariff. In the group of respondents who never chose the status quo but not always the maximum discount, the WTA for a control of appliances is always negative. This means that they demand a lower overall compensation when choosing a TOU tariff. For them a control of certain appliances is a benefit or a service. Overall, this is evidence that respondents who chose a TOU tariff prefer a control of certain appliances to avoid electricity usage in times with high electricity prices.

Turning to potential non-purchasers of TOU tariffs, we identify extreme WTA values (see Table 6). Respondents who always seek a maximum discount might exhibit a large marginal utility of discount (see panel (d) in Figure 2), and probably ignore all other attributes. These respondents are unlikely to purchase a TOU tariff if their monthly discount amounts to such low values. A similar argument holds for respondents who always choose a fixed rate tariff (the status quo). They might indeed exhibit a marginal utility of discount close to zero (see panel (c) in Figure 2). For them the marginal WTA for peak times on weekdays (see Table 6) exceeds average monthly electricity costs of a German household. They are unwilling to adapt their electricity demand regardless of the monetary savings.

In the following, we focus on shifting electricity demand at peak times by controlling electricity consumption of appliances. For this, we focus on the potential TOU tariff purchasers. To illustrate potential shifts in electricity demand, we calculate how many respondents would be willing to accept a control of appliances' electricity consumption. Figure 3 illustrates the kernel density estimates of individual WTA by appliance and respondent group. The continuous line shows the densities for the group without a dominant decision strategy; the discontinuous line shows the densities for the group who never chooses a fixed rate tariff, but not always the maximum discount. For both groups, we estimate WTA values ranging in a large interval around zero. Note that density scale dimensions differ by appliance.

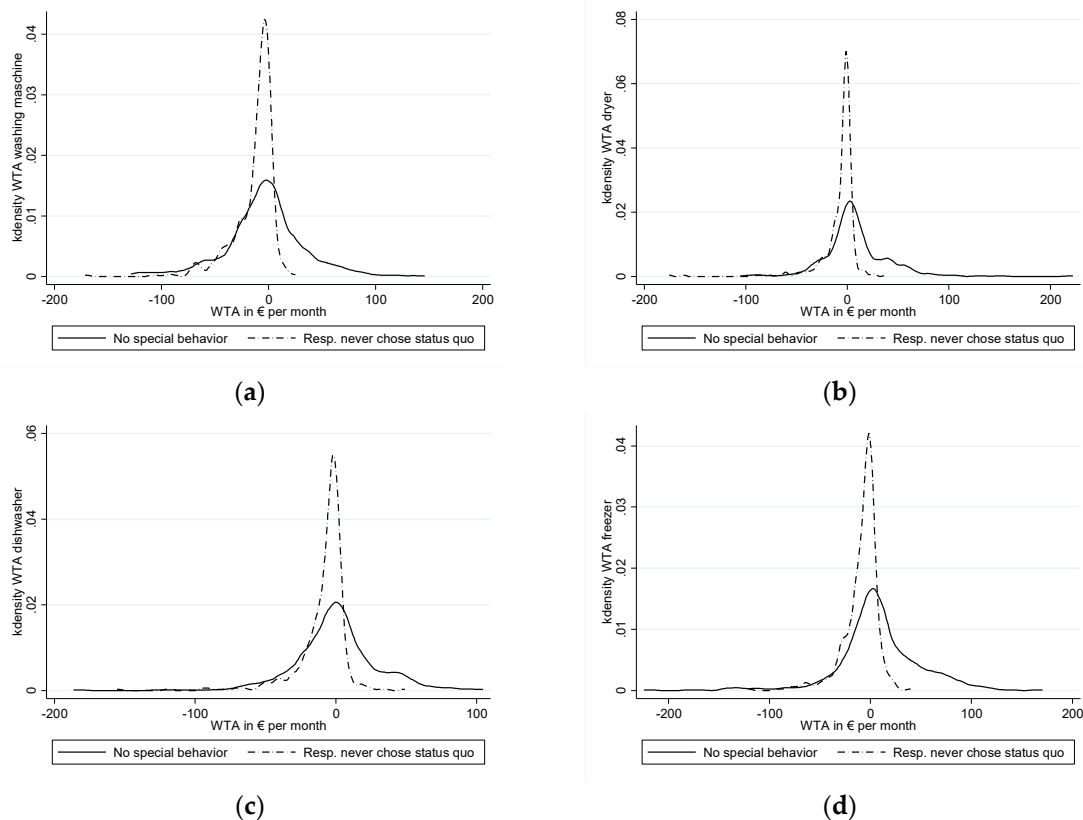


Figure 3. Kernel density estimates of conditional WTA by respondent groups and appliance. Continuous line: respondents without dominant strategy. Discontinuous line: respondents who never chose the status quo but not always the maximum discount. (a) Washing machine; (b) dryer; (c) dish washer; (d) freezer.

Assuming that respondents with a negative WTA (lower overall compensation) would accept a control of electricity consumption of their appliances, over 80% of those who never choose a fixed rate tariff, and over 50% of those who reveal no dominant decision strategy would accept a control of their washing machine's electricity consumption. This share almost sums up to 50% of our total sample including non-purchasers. The potential of decreasing electricity demand in peak times by controlling electricity consumption of the other appliances is lower (39–44% of our total sample), but still meaningful.

5. Scenario Analysis

In this section, we use a scenario analysis to make a back-of-the-envelope calculation to illustrate the amount of megawatt hours (MWh) that could be saved in Germany by means of a control of

washing machines, dryers, and dishwashers during peak times for potential TOU tariff purchasers. We use a back-of-the-envelope calculation with simplifying assumptions for illustration.

First, based on our results we assume that a maximum of 70% of all households are potential TOU tariff purchasers. To illustrate the potential shift in electricity demand, we created four scenarios. These differ by the shares of TOU tariff purchasers accepting a control of their appliances, i.e., 25%, 50%, 75%, and 100% (of the identified 70% of all households). Second, Germany has roughly 80 million inhabitants consuming 127 billion MWh per year [29]. An average household has two persons, meaning Germany has about 40 million households. Using our first assumption, a maximum of 28 million households (70%) would purchase a TOU tariff. Third, we do not know when and how long households use their appliances. Although being overly simplistic, we assume that appliance usage is uniformly distributed over the day, and thus, the probability of using an appliance during peak hours (assuming it lasts four hours a day) is 1/6. Additionally, we assume that each appliance is used for one hour.

Table 7 provides an overview of consumers' appliance usage based on the published results [30] and our assumptions. The number of appliance owners are given by the respective share in our sample. Mean electricity consumption of appliances is taken from the estimates by Frondel et al. [30]. In the same survey, consumers stated their appliance usage in their household. We used this data to calculate the average number of appliance usages in million per day and per peak time.

Table 7. Data used to estimate shifts in electricity demand.

Appliance	Owners ¹	Consumption of Appliance (in kWh Per Usage) ²	Mean Yearly Usage Per Household ³	Daily Usage (in Mio Appliances)	Peak Time Usage (4 Hrs a Day) (in Mio Appliances) ⁴
Washing machine	95.85%	0.68	185	19.43	3.24
Dryer	45.35%	2.79	98	4.87	0.81
Dishwasher	74.89%	1.27	186	15.27	2.544

Note: ¹ Share of households in our sample in which appliance is available. ² Estimated using ordinary least squares by Frondel et al. [30]. ³ Data based on a German household survey by Frondel et al. [30]. ⁴ We assume that the probability of using an appliance is uniformly distributed over the day.

Knowing how many appliances households use during peak times, and how much electricity is on average consumed by this kind of appliance allows us to approximate the potential shift in electricity demand during one-hour peak time (see Table 8). Based on our scenarios, changes in demand would vary between 337 MWh in the 25%-Scenario and 1347 MWh in the 100%-Scenario. To illustrate the size of this effect, the change in demand corresponds to the installed capacity of a small (scenario 1) to large-sized (scenario 4) fossil-fuel power plant (about 1000 MW).

Table 8. Potential shift in electricity demand by scenarios.

Scenario ¹	Households Accepting Control (in Mio)	Shifted Demand during One Peak Time Hour in MWh			
		Washing Machine	Dryer	Dishwasher	Total
(1) 25%	7	96	99	141	337
(2) 50%	14	193	198	283	674
(3) 75%	21	289	297	424	1010
(4) 100%	28	385	396	565	1347

Note: ¹ Scenarios differ by their share of TOU tariff purchasers (here: 70% in households) who accept a control of appliances.

6. Discussion and Conclusions

Knowledge about consumer preferences for TOU tariffs is still insufficient. Based on a large sample of the German population, we use a CE with TOU tariffs to estimate the effect of different peak time schemes on private consumers' WTA. These tariffs allow for additional (dis-)services during peak times, i.e., controlling electricity consumption of specific appliances. We find that taste heterogeneity among respondents is significant identifying four groups with mutual exclusive strategies in decision-making.

In general, we verify previous findings that TOU tariffs on average decrease consumers' utility (e.g., [8]). However, taste heterogeneity constitutes an influential factor when estimating consumers' WTA. MXL models account for unobserved heterogeneity but neglect the effect of decision strategies on WTA's variance. We show that decision strategies largely explain the variance. For example, a significant share of respondents always neglects inconveniences of peak time pricing, a smaller share reacts only to discounts. Estimating WTA for these two groups of respondents results in extreme WTA values. Low energy literacy might explain part of this. Blash et al. [31] suggests that low energy literacy could cause other decision strategies than maximization behavior, since they found that consumers with a low energy literacy acted boundedly rational when facing a decision on a more energy efficient appliance. We, therefore, expect utility companies to face serious difficulties to incentivize those two groups of customers to choose TOU tariffs.

Still, we identify 70% in our sample as potential TOU tariff purchasers of which 36% never chose a fixed rate tariff. The latter percentage is in line with the findings based on a meta-analysis; up to 43% of customers would opt for TOU tariffs given significant benefits [7]. In our CE, we provided significant discounts and a control of appliances. Our results suggest that most consumers demand high compensational payments to accept TOU tariffs but might benefit from a control of appliances. We, therefore, recommend electricity providers to offer TOU tariffs including those benefits, and suggest decision-makers to force smart meter roll out and to encourage purchases of smart appliances. An increasing share of consumers purchasing TOU tariffs could lead to a significant shift in electricity consumption from peak times to off-peak times, and therefore a cost reduction in redispatch. Obviously, the share in households accepting a TOU tariff would be lower if electricity providers chose a lower discount than the ones considered in our CE. Future studies might therefore focus on real world experiments to overcome the hypothetical situation of a CE.

A limitation of our analysis might be that not all households use all the devices we presented on the choice cards. While next to every household has a washing machine, half of the households do not have a dryer, for example. A consequence could be that our estimates are biased because of the attribute non-attendance. As the treatment of non-attendance is not agreed on in the literature, we decided not to apply models such as the equality-constrained latent class model in order to account for non-attendance. Future studies might use dynamic questionnaires that would allow to only incorporate those devices the responding household is using. Furthermore, they might also investigate sources of heterogeneity in more detail by, for example, applying qualitative methods such as think aloud protocols and a larger series of focus groups.

Our scenario analysis suggests that TOU tariffs could be a significant measure to reduce the need to generate electricity by shifting demand. However, our analysis is based on a simple back-of-the-envelope calculation assumption for example that the use of appliances is uniformly distributed. We might thus overestimate the shift in electricity consumption and subsequently the potential benefits on the supply side. It was not the objective of this study to investigate comprehensively the effects of potential demand shifting on electricity markets. Future studies, however, should account for them as they might diminish the positive effects suggested by this analysis.

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Appendix A

Translation of the Information Given before the Choice Experiment

There is currently a discussion in Germany about the future of the energy transition. Among other things, consumption should be reduced at times of the day when it is particularly high, e.g., in the morning when many people have got up. The high consumption must be compensated for during these times by electricity from additional gas- and coal-fired power plants. These power plants are only needed during these times and therefore cause high costs.

For this reason, consideration is being given to adjusting the price of electricity at times of high electricity consumption (peak times). In peak time (PT) the price of electricity would be higher than usual, in the off-peak time (OT) the electricity price would be lower than usual.

We show you several selections of electricity tariffs on the following pages. Please imagine that you can only select one of the three electricity tariffs in each selection. Please indicate the tariff you would choose in these circumstances.

To begin with, we will introduce you to the tariff attributes on the next page.

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