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Preferences for dynamic electricity tariffs: A comparison of households in Germany and Japan

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Abstract

We evaluate a stated choice experiment on dynamic electricity tariffs based on two representative household surveys from Germany and Japan. Our results indicate significant differences between German and Japanese respondents' preferences towards dynamic tariffs, with the latter generally being more open to dynamic pricing. Furthermore, our unique experimental design allows to disentangle preferences for inter- and intraday price changes, which are two essential tariff characteristics. In this respect, our results suggest that households need significant compensation in order to accept frequently changing price patters. In contrast, they are mostly indifferent with respect to the number of price changes per day. Besides the implementation of an environmental treatment message, we additionally investigate tariff characteristics, which aim at overcoming household acceptance barriers. To this end, a restrictive use of households' consumption data, price caps, as well as highlighting the environmental benefits associated to dynamic tariffs present themselves as suitable tools to reduce households' aversions against dynamic electricity tariffs.

Keywords: Dynamic electricity tariffs, Stated choice experiment, Household acceptance barriers, Tariff design

JEL classification: C35, D12, Q41

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1. Introduction

To achieve the goals of the Paris Climate Agreement, countries around the world are taking action to reduce their greenhouse gas (GHG) emissions. To this end, a particular focus is being placed on the energy sector, which alone was responsible for more than one-third of global GHG emissions in 2020 (Olivier et al., 2021). Naturally, rapidly growing shares of renewable energy sources are contributing to the reduction of GHG emissions. However, they also lead to more volatile electricity production, which stresses the stability of electricity grids and increases the need for demand-side management. In this context, dynamic electricity tariffs are a frequently discussed instrument to balance electricity supply and demand (e.g. Dutta and Mitra, 2017). With dynamic electricity tariffs, price signals incentivize shifts in electricity consumption to more favourable time zones. Thereby, dynamic pricing schemes not only support grid stability (Gelazanskas and Gamage, 2014) but also reduce demand for costly peak capacity (Faruqui et al., 2010) and foster the integration of renewable energy sources (Brouwer et al., 2016).

Generally speaking, the adoption of dynamic electricity tariffs is considered to increase overall economic efficiency, as the total generated economic value increases (e.g. Borenstein, 2005). In line with microeconomic theory, dynamic electricity tariffs maximize economic efficiency when they reflect the short-run social marginal costs of electricity generation (Borenstein, 2016). To this end, real-time-pricing (RTP) tariffs are considered the 'purest form' of available dynamic pricing schemes, with electricity unit prices changing hourly or even more frequently (e.g. Buryk et al., 2015). However, despite the many benefits being associated with RTP tariffs, including monetary savings for customers (Allcott, 2011), residential consumers typically prefer constant electricity prices and would thus require significant compensation to switch to RTP tariffs (e.g. Ruokamo et al., 2019). In fact, the results of Leautier (2014) suggest that if household participation costs are taken into account, economic welfare associated with the uptake of dynamic tariffs could even decrease.

Against this background, the findings of Holland and Mansur (2006) are worth noting. They show that time-of-use (TOU) tariffs, which have fixed price levels for peak (day) and off-peak (night) hours, can capture a significant share of the overall economic efficiency gains associated with RTP tariffs. This is relevant as residential customers typically prefer TOU tariffs over RTP tariffs (e.g. Schlereth et al., 2018; Dütschke and Paetz, 2013; Yoshida et al., 2017). Hence, when we consider household participation costs, the adoption of TOU tariffs could potentially lead to greater economic efficiency than RTP tariffs.

TOU and RTP tariffs differ in two central features. While the former typically comprises two price zones each day (day and night) with fixed price levels over a year (or at least a month), the latter typically entails 24 price zones each day (hourly) that involve daily changing price levels (e.g. Dutta and Mitra, 2017). To the best of our knowledge, no existing research has yet disentangled the effects of these characteristics on household preferences for TOU over RTP tariffs. However, this is important because to optimize economic efficiency that accounts for household participation costs, we must consider household preferences for – or rather, aversions against – price changes within a day and across days separately.

We address this gap in the understanding of consumer preferences for dynamic electricity tariffs using a stated choice experiment conducted in Germany and Japan. Both countries are highly developed and among the world's five largest economies in 2020 (World Bank, 2022). However, they differ significantly in terms of the structure of their energy systems as well as the technological feasibility of dynamic tariffs. For example, while Germany produced well over 40 % of its electricity from volatile renewable energy sources in 2020, Japan's electricity production from renewables was only around 25 % (Ritchie and Roser, 2021). Nonetheless, the rollout of smart meters, being a necessary prerequisite for dynamic tariffs (Wolak, 2011), is well advanced in Japan, but still in its infancy in Germany (Sovacool et al., 2021). At the same time, the latest UN survey on peoples' climate perception (Fisher et al., 2021) revealed that a similar share of German (77 %) and Japanese (79 %) respondents consider climate change a global emergency. However, within these two groups the support for urgent and comprehensive actions to tackle climate change is higher among the German (73 %) compared to the Japanese (62 %) sample. In particular, the differences in the availability of technology and general support for urgent climate measures render the comparison of the two countries in this study highly relevant.

Moreover, given the results of Buryk et al. (2015) that knowledge about the environmental benefits of dynamic tariffs significantly reduces household aversion to them, we implement an environmental treatment in our survey. Unlike respondents in the control group, respondents in the treatment group received additional information that a larger number of price zones, as well as a higher frequency of price updates, increase the environmental benefits possible with dynamic tariffs. Using this treatment, we can investigate whether information about environmental benefits casually influences the preferences for dynamic electricity tariffs. Based on our findings we provide useful guidance to policymakers on how to design and exploit the potential of dynamic electricity tariffs in terms of both economic efficiency and environmental benefits.

The remainder of the paper is organised as follows. Section 2 reviews the related literature and provides necessary background information. Section 3 describes the experimental design, the survey data, and our empirical strategy. Section 4 presents and discusses the results as well as the limitations of our study. Finally, Section 5 presents the conclusions and implications of our study.

2. Literature review

The capability and willingness of households to shift their electricity consumption in response to price signals has been investigated in several field studies. While most report residential peak load reductions of about 10 % (e.g. Wolak, 2011; Stamminger and Anstett, 2013) to 15 % (e.g. Shariatzadeh et al., 2015; Faruqui et al., 2010), Davis et al. (2013) suggest that overall electricity consumption is typically not reduced. Conducting a framed field experiment in the US, Jessoe and Rapson (2014) identify the formation of conservation habits when observing long-term responsiveness to dynamic pricing. However, the field experiment most relevant to our study was conducted by Wolak (2011) when comparing the response behaviour of US households to RTP and critical peak pricing (CPP). His findings suggest that exposing customers to a larger number of price periods per day does not reduce their capability or their willingness to shift electricity consumption. This could indicate that any household aversion to RTP tariffs primarily relates to the higher frequency of general price updates and not the number of time zones per day.

A growing body of literature also analyses the increase in economic welfare associated with the uptake of RTP tariffs (e.g. Borenstein, 2005; Holland and Mansur, 2006) and discusses the implications for optional tariff design (e.g. Borenstein, 2016; Burger et al., 2020). However, as rightly pointed out by Gambardella et al. (2019), household participation costs should be included in the assessment of overall welfare, particularly because households require significant compensation to switch to a dynamic tariff to keep their utility level constant (e.g. Ruokamo et al., 2019).

Given dynamic electricity tariffs are not common in either Germany or Japan, we can best elicit the utility households derive from such tariffs using stated preferences. In this respect, we build upon a small but increasing number of studies. Based on a stated choice experiment (SCE) conducted in Finland, Ruokamo et al. (2019) estimate respondents' willingness to accept (WTA) RTP tariffs at about €78 annually, which they associate with the high level of discomfort associated with the uncertainty in electricity costs, along with the unwillingness of respondents to shift electricity consumption. This is also in line with the findings of Schlereth et al. (2018) from a SCE conducted among customers of a German electricity provider. In general, they find that respondents preferred static (flat) tariffs the most. However, they also show that customers favoured TOU tariffs over RTP because of the 'unpredictable' price variations of the latter. Schlereth et al. (2018) also identify cost insurances, i.e., price caps, as a useful tool for increasing the preferences for dynamic tariffs. Based on a SCE conducted with over 4000 electricity customers in Japan, Yoshida et al. (2017) find similar results, namely that residential customers prefer TOU over RTP tariffs.

In one of the first SCEs on dynamic tariffs, also Dütschke and Paetz (2013) show that German households prefer TOU tariffs over RTP, even though they are generally unaware of most of the benefits associated with dynamic tariffs. The latter finding corresponds with Buryk et al. (2015), who conclude that preferences for dynamic electricity tariffs increase when respondents from the US and EU have additional knowledge about the environmental benefits of these tariffs. Related choice experimental studies from Japan (e.g. Nakai et al., 2018; Morita and Managi, 2015; Murakami et al., 2015) and Germany (e.g. Fait et al., 2022; Mengelkamp et al., 2019; Kaenzig et al., 2013) consistently conclude that residential electricity consumers are willing to pay a price premium for electricity produced from renewable energy sources.

To our best knowledge, this is the first study to analyse various levels of consumption data usage with respect to dynamic electricity tariffs. Based on a SCE on smart meter technologies, Pepermans (2014) observe that sharing electricity consumption data with third parties does not reduce Flemish household preferences for smart metering devices. This contrasts with Richter and Pollitt (2018), who reveal that respondents require significant compensation for sharing their electricity consumption data with third parties, such that the need for compensation is even greater when sharing personally identifying data.

Based on the above-mentioned literature, there is an indication that differentiation between the frequency of price updates and the number of time zones each day is highly relevant. Evidence from revealed preferences also suggests that the daily price variations associated with RTP tariffs could be more problematic than the simple number of time zones. Moreover, we can build upon existing studies to predict that providing respondents with additional information on the environmental benefits associated with dynamic electricity tariffs will significantly reduce any aversion to dynamic electricity pricing.

3. Data and methodology

3.1. Survey overview

We conducted representative surveys of private households in Germany and Japan in cooperation with two professional market research institutes: Psyma + Consultic GmbH for the German survey from April to May 2021, and MyVoice Communications, Inc., for the Japanese survey in March 2020. A two-tiered sampling strategy was employed. First, the market research companies recruited people according to quotas for age, gender, and inhabited area for the general German[1] and Japanese population. Second, we asked respondents if they were financial decision makers deciding alone or with other household members on major expenditures like buying a new fridge or car or choosing a new electricity contract. Only these were eligible to participate in the survey. Furthermore, the survey companies conducted several quality checks to ensure that only qualified responses were received.

The survey comprised four parts. First, we questioned respondents about their individual attitudes, traits, and values. Second, we asked them about their current electricity contract and their electricity consumption behaviour. Third, and most importantly, we implemented a SCE on dynamic electricity tariffs. Finally, we queried respondents about their sociodemographic characteristics including household size, personal status, and income.

3.2. Stated choice experiment

SCEs elicit respondents' preferences for a set of alternatives expressed by a bundle of attributes with varying levels (e.g. McFadden, 1973). Typically, they are used to evaluate products or services that either do not yet exist or are not available in the market for all variants of interest (Holmes et al., 2017). In our experiment, respondents answered six consecutive choice tasks on dynamic electricity tariffs. In each choice task, we asked respondents to choose between three dynamic electricity tariffs and their current electricity tariff, the so-called status quo option. If a respondent selected the status quo option in their first choice, we added a second choice to each choice task in which the respondent could choose only among the three dynamic tariffs. The first and second choices in each choice task represent an unconditional and a conditional design, respectively.

The dynamic tariffs and the status quo option were specified by six attributes: *number of time zones*, *price update*, *potential savings*, *necessary shift of consumption*, *cap for additional costs*, and *data utilization*. An overview of the selected attributes and their levels is presented

[1]The German sample is additionally representative in terms of the high school graduation rate.

in Table 1. Table 2 presents an example choice task for the unconditional design. In the conditional design, the 'my current tariff' option is omitted.

Table 1: Overview of attributes and levels

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5
Number of time zones	1[a]	2	4	12	24
Price update	Yearly	Monthly	Weekly	Daily	
Potential savings (shown in € or JPY)	0 %[a]	5 %	10 %	15 %	
Necessary shift of consumption	0 %	5 %	10 %	15 %	
Cap for additional costs (shown in € or JPY)	5 %	10 %	15 %	No cap for additional costs	
Data utilization	Cost accounting only	Cost accounting and data analysis	Cost accounting, data analysis and data shared with third parties		

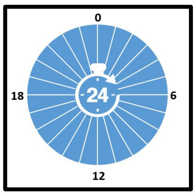
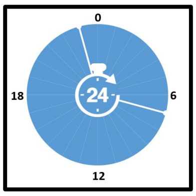
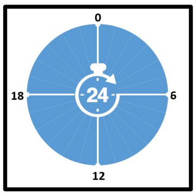
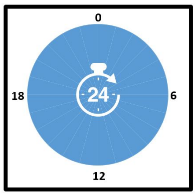
Notes: [a]This level was only shown in the status quo option.

In contrast to previous studies (e.g. Schlereth et al., 2018; Yoshida et al., 2017; Buryk et al., 2015; Dütschke and Paetz, 2013), we disentangle RTP and TOU tariffs based on two attributes. The first, *number of time zones*, denotes the number of different prices within a day. In our survey, this attribute has five levels: 1 time zone (only shown in the status quo option), 2 time zones, 4 time zones, 12 time zones, and 24 time zones, respectively. In both surveys, we included the number of time zones of respondents current electricity contract in the status quo option, as we expect that a certain number of respondents currently use an electricity tariff with more than one time zone.[2]

The second attribute, *price update*, reveals how often the price for one unit of electricity is updated and communicated to consumers. In the choice experiment, this attribute is characterized by four levels: yearly, monthly, weekly, and daily. A monthly update, for example, means that consumers receive information on the price of electricity in each time zone monthly, i.e. during each month the price pattern repeats every day. In Japan, price

[2]In fact, 13 % of Japanese (8 % of German) respondents answered that they currently have a contract with two time zones.

Table 2: Exemplary choice task

	Tariff 1	Tariff 2	Tariff 3	My current tariff
Number of time zones	 24	 2	 12	 1
Price update	Daily	Monthly	Weekly	Yearly
Potential savings	€6	€9	€3	€0
Necessary shift of consumption	5 %	15 %	5 %	0 %
Cap for additional costs	No cost cap	€6	€3	No cost cap
Data utilization	Cost accounting, data analysis and data shared with third parties	Cost accounting and data analysis	Cost accounting, data analysis and data shared with third parties	Cost accounting only
I chose:	☐	☐	☐	☐

changes are rather frequent. Therefore, we set a monthly price update for the Japanese status quo option. With respect to the German survey, the level of this attribute in the status quo option was again customised to the respondents' current electricity tariffs.

As third attribute, we included *potential savings*, which indicates how much money a household can save per month when selecting the corresponding electricity tariff. We divided the potential savings into four levels: 0 %, 5 %, 10 %, and 15 %, with 0 % occurring only in the status quo option. Prior to the choice experiment, we surveyed respondents about their current monthly electricity costs. Based on this information, we provided the potential savings (in EUR or JPY) individually for each respondent by multiplying their monthly electricity costs with the applicable level of potential savings.

However, given these savings are generally only possible if the household shifts part of its electricity consumption from time zones with high prices to time zones with low prices, our fourth attribute, *necessary shift of consumption*, indicates how much of daily electricity consumption must be shifted to achieve the financial savings. Here, the four levels vary between 0 %, 5 %, 10 %, and 15 %. For each level, we provided respondents with examples about the actions on their part required to achieve the necessary shift of consumption. For instance, if consumers need to shift 5 %, one large-scale appliance such as a washing machine or a dishwasher must only be used in time zones with low prices. In addition, we told respondents that their electricity costs may also increase if they do not react or react wrongly to price changes in the different time zones.

One way to limit such cost risk is to set a cost cap, which is reflected in our fifth attribute, *cap for additional costs*. The attribute has four levels: no cap for additional costs, maximum 5 % additional costs, maximum 10 % additional costs, and maximum 15 % additional costs. As with potential savings, we provided the levels individually for each respondent in EUR or JPY per month based on households current electricity costs. In addition, we informed respondents that maximum additional costs refer to constant total electricity consumption.

Finally, the sixth attribute, *data utilisation*, specifies how the electricity consumption data can be used by the electricity supplier. The three levels are cost accounting only, cost accounting and data analysis, and cost accounting, data analysis, and data shared with third parties. In the third level, in addition to billing purposes and data analysis, the contract provider can share consumer data with third parties that have nothing to do with electricity generation or supply. We included this attribute in our experiment because several studies have shown that privacy concerns play an important role in households decision making, especially for energy-related services and products (e.g. Pepermans, 2014; Richter and Pollitt, 2018).

To ensure that respondents understood all attributes correctly, we explained the attributes in detail before the experiment. In addition, respondents needed to correctly answer several quiz questions about the attributes following the explanations. If they failed to answer these questions even after two repetitive loops, they were excluded from the analysis.

3.3. Explanatory variables

We considered several explanatory variables for the econometric analysis outlined in Section 3.4. In terms of sociodemographic characteristics, we control for respondents' age in years ('age'), their gender ('female'), whether respondents are married ('married'), and whether they hold at least a bachelor's degree ('university degree'). We also control for the number of household members ('household size'), the number of children living in the household ('no. of children'), and the weighted monthly household income in EUR ('household income').[3]

To measure individual environmental attitudes, we build upon the New Ecological Paradigm (NEP) developed by Dunlap et al. (2000). While the original scale comprises 15 items, we follow the suggestion of Whitmarsh (2008), who found that respondents had difficulty answering 9 of 15 items, and use a shortened six-item scale. Furthermore, we follow Ziegler (2017) and construct six binary indicators, each of which takes a value of one if respondents 'agree' or 'strongly agree' with one of the three corresponding positively framed statements and likewise 'disagree' or 'strongly disagree' with one of the three negatively framed statements. Finally, we use the sum of these six binary indicators to approximate respondents' environmental attitudes, with higher values indicating higher environmental awareness.

We utilise the survey items developed by Falk et al. (2016, 2018) to assess respondents' economic preferences. To measure risk preferences, we asked respondents to what extent they are generally willing to take risks on a five-point scale. If a respondent chose either 'rather willing' or 'very willing', the corresponding binary variable 'risk seeking' takes a value of one. In the same manner, we create a dummy variable 'patient', if respondents indicated they are either 'rather patient' or 'very patient' when asked how patient they are in general. Finally, the binary variable 'generous' takes a value of one when respondents answered the question how generous they are in general, by indicating 'rather generous' or 'very generous' on a five-point scale. By contrast, the variable 'trusting' ranges from 0 to 3 as it builds upon three survey items. 'Trusting' is the sum of three binary variables, each of which takes the value one if we consider the respondents' answers to the corresponding trust measuring statements as 'trusting' or 'very trusting'.

Finally, we also specify variables relating to household electricity consumption and prior tariff choice behaviour. We include a binary variable that takes a value of one if respondents actively changed their electricity tariff at least once in the last ten years. Another binary indicator takes a value of one if households' heating systems rely on electrical heating devices.

[3]Respondents provided their monthly net household income across ten income classes. Using the mean values of the classes, we created a continuous variable. In line with Feldman (2010), we set the last class 1.5 times its lower boundary. Based on this variable, we calculate the weighted household income by dividing household income by the square root of the number of household members. This so-called square root scale is one of several available instruments to construct weighted income variables. For an overview, see Atkinson et al. (1995). Finally, we converted the Japanese classes into EUR based on the average exchange rate for 2020: 1 EUR = 121.85 JPY (https://t1p.de/gezmg; accessed 14.02.2022).

Furthermore, we control for the average time that any household member is at home during the day, which allows for manual load shifting.

Table 3: German sample: summary statistics by treatment

	Baseline				Treatment				
	Count	Mean	SD	Min-Max	Count	Mean	SD	Min-Max	P-value
Environmental attitudes	516	4.76	1.49	0-6	543	4.80	1.54	0-6	0.318
Trusting	516	0.87	0.94	0-3	543	0.87	0.97	0-3	0.960
Risk seeking	516	0.34	0.48	0-1	543	0.31	0.46	0-1	0.270
Generous	516	0.67	0.47	0-1	543	0.66	0.47	0-1	0.949
Patient	516	0.56	0.50	0-1	543	0.56	0.50	0-1	0.994
Age	516	50.17	16.79	18-85	543	49.94	16.20	18-91	0.804
Female	516	0.51	0.50	0-1	543	0.47	0.50	0-1	0.193
Household income[a]	516	1.88	0.93	0.18-8.66	543	1.98	1.27	0.13-15.00	0.476
University degree	516	0.17	0.38	0-1	543	0.14	0.35	0-1	0.146
Married	516	0.49	0.50	0-1	543	0.49	0.50	0-1	0.989
Household size	516	2.22	1.13	1-10	543	2.22	1.18	0-9	0.624
No. of children	516	0.28	0.65	0-6	543	0.29	0.70	0-5	0.743
Average time at home	516	17.66	6.28	2-24	543	18.09	5.84	2-24	0.350
Electric Heating	516	0.12	0.32	0-1	543	0.12	0.33	0-1	0.796
10-years tariff change	516	0.64	0.48	0-1	543	0.63	0.48	0-1	0.740

Notes: [a]Weighted household income in 1.000 Euro. P-values in the last column refer to Pearson's chi-squared test for independence between the treatment groups in case of binary variables and to the Kruskal-Wallis equality-of-populations rank test for non-binary variables.

We present descriptive statistics for the German and Japanese samples in Tables 3 and 4, respectively. For each variable, the p-value in the last column corresponds to a test for statistical difference between the baseline and the treatment group. Except for the variable 'household size' in the Japanese sample, there are no statistically significant differences between the baseline and the treatment groups, which suggests successful randomisation in both surveys.

Tables A.1 and A.2 in the Appendix show the summary statistics by treatment, with p-values referring to statistical differences across countries. From both tables, it is apparent that several variables vary significantly between the two samples. Most importantly, German respondents have, on average, significantly higher environmental attitudes. They are also more trusting, risk seeking, and generous compared with Japanese respondents. Regarding the sociodemographic characteristics, Japanese respondents are younger, are more often married, have significantly higher household income, and are more frequent holders of at least a bachelor's degree.

Table 4: Japanese sample: summary statistics by treatment

	Baseline				Treatment				
	Count	Mean	SD	Min-Max	Count	Mean	SD	Min-Max	P-value
Environmental attitudes	1348	3.73	1.86	0-6	1334	3.73	1.82	0-6	0.879
Trusting	1348	0.52	0.75	0-3	1334	0.49	0.74	0-3	0.235
Risk seeking	1348	0.16	0.37	0-1	1334	0.17	0.37	0-1	0.863
Generous	1348	0.48	0.50	0-1	1334	0.47	0.50	0-1	0.777
Patient	1348	0.54	0.50	0-1	1334	0.55	0.50	0-1	0.681
Age	1348	45.56	13.53	20-69	1334	45.75	13.59	20-69	0.720
Female	1348	0.51	0.50	0-1	1334	0.52	0.50	0-1	0.721
Household income[a]	1348	3.95	2.74	0.34-15.39	1334	4.07	2.88	0.34-15.39	0.638
University degree	1348	0.53	0.50	0-1	1334	0.53	0.50	0-1	0.859
Married	1348	0.61	0.49	0-1	1334	0.59	0.49	0-1	0.463
Household size	1348	2.70	1.29	1-10	1334	2.61	1.28	0-8	0.070
No. of children	1348	0.33	0.73	0-5	1334	0.32	0.71	0-4	0.879
Average time at home	1348	18.37	5.50	2-24	1334	18.27	5.72	2-24	0.686
Electric Heating	1348	0.53	0.50	0-1	1334	0.52	0.50	0-1	0.949
10-years tariff change	1348	0.32	0.47	0-1	1334	0.33	0.47	0-1	0.495

Notes: [a]Weighted household income in 1.000 Euro. P-values in the last column refer to Pearson's chi-squared test for independence between the treatment groups in case of binary variables and to the Kruskal-Wallis equality-of-populations rank test for non-binary variables.

3.4. Empirical approach

In this paper, we analyse a SCE containing three unlabelled alternatives with six randomised attributes and a status quo option where attribute levels were constant for each surveyed individual. In both surveys, those for Germany and Japan, we implemented identical baseline messages and an environmental treatment. This allows us to compare results across samples and additionally investigate country-specific treatment effects.

To obtain first insights into respondents' choice behaviour, we investigate how often they choose any of the three dynamic tariffs over the status quo alternative at the individual level. The corresponding dependent variable 'frequency', which counts from zero to six, is analysed using Tobit regression. Furthermore, we use probit regressions to analyse the determinants of the likelihood of either 'always' or 'never' choosing a dynamic tariff. In all three models, we include a treatment dummy as well as the individual specific characteristics discussed in Section 3.3 as control variables. We additionally include all control variables as country-interaction terms to investigate sample-specific differences.

To address the central aim of this paper, we analyse the SCE in more detail. To this end, we conduct a 2×2-split sample (country×treatment) analysis. Thereby, we can analyse country differences in the baseline, as well as country-specific treatment effects. Given the two samples differ in their average status quo characteristics, we restrict our analysis to the conditional design (i.e., without the status quo option).[4] Thereby, we can conduct a clean comparison of the relative preferences for specific attribute levels across countries.

In line with the random utility maximisation theory developed by McFadden (1973), we assume that respondents will choose a particular electricity tariff within a choice situation if the utility associated with this tariff is larger than those of all remaining alternatives. The corresponding hypothetical utility U that respondent $i\,(i = 1, ..., N)$ derives from choosing tariff $j\,(i = 1, ..., 3)$ in choice situation $m\,(m = 1, ..., 6)$ can be expressed as follows:

$$U_{ijm} = \beta_i' x_{ijm} + \epsilon_{ijm}, \tag{1}$$

where x_{ijm} is a vector of explanatory variables (with $x_{ijm} = x_{ijm1}, ..., x_{ijmK}$) and β_i refers to the corresponding vector of unknown parameters (with $\beta_i = \beta_{i1}, ..., \beta_{iK}$). We rely on commonly used mixed logit models to estimate the unknown parameters, which comprise all attributes and two alternative-specific constants to control for a potential left–right bias (e.g., discussed by Hess and Hensher, 2012). In contrast to multinomial logit models, the mixed logit model is independent of the IIA (independence of irrelevant alternatives) assumption. Furthermore, mixed logit models allow preference heterogeneity between individuals and thus can cope with correlations between choice alternatives. This is particularly important in our case, as respondents make six sequential choices. The preference heterogeneity is expressed by the assumption that the random parameters are continuously distributed across i (e.g. Gutsche and Ziegler, 2019):

$$\beta_{ik} = \beta_k + \sigma_k\, u_{ik}, \tag{2}$$

where σ_k represents the standard deviation of the distribution of β_{ik} around the mean β_k and $u_{ik} \sim N(0, 1)$ captures the individual specific heterogeneity. We specify the parameters for all non-financial attributes to be random and, in line with common practice (e.g. Schwirplies et al., 2019; Gutsche and Ziegler, 2019), the parameter for the financial attribute to be fixed.

Building upon the discussed model specification, we estimate the marginal rates of substitution between the financial attribute and the remaining tariff characteristics. Within the

[4]Respondents that initially chose the status quo option subsequently had to indicate the tariff they preferred the most among the three remaining alternatives. As discussed by Boyle and Özdemir (2008), an alternative that maximises utility in a choice situation that includes a status quo option will also maximise utility in a choice situation without. Therefore, we can consider the initial and subsequent choices of dynamic tariffs jointly in a model that excludes the status quo option.

assumed linear additive indirect utility function, the ratio of the partial derivatives corresponding to the rate of substitution equals the ratio of the estimated parameters (Hoyos, 2010). Consequentially, we can estimate the mean marginal WTA[5] for a specific attribute (level) as follows:

$$WTA = \frac{-E(\beta_k)}{\beta_c}, \tag{3}$$

where $E(\beta_k)$ refers to the mean parameter of the non-cost attribute and β_c to the parameter of the cost attribute (Hole, 2007a). In line with Glenk et al. (2019), we use the Krinsky and Robb (1986) bootstrapping approach to calculate the corresponding confidence intervals and utilise the complete combinatorial test proposed by Poe et al. (2005) to compare the estimated mean marginal WTA values across countries and treatments. We conduct all estimations with Stata 14.

4. Results and discussion

4.1. Frequency and likelihood of choosing a dynamic tariff

Table 5 reports by country and treatment the descriptive statistics for the frequency of situations in which respondents chose a dynamic tariff, along with the share of respondents who 'always' or 'never' choose a dynamic tariff. Figure A.1 in the Appendix visualises the distribution of the choice frequency, which naturally also includes 'never' and 'always' choosers, by country and treatment.

The general choice behaviour of respondents is very similar for the three variables. In the baseline, respondents from Germany (Japan) choose the dynamic tariff in 70.9 % (70.3 %) of the choice situations, which translate into a frequency of 4.256 (4.218) (out of 6). Across all four groups, approximately 50 % of respondents always choose a dynamic tariff, whereas roughly 15 % consistently refuse them. The only significnat difference is the higher frequency in which respondents, when faced with the environmental treatment, choose a dynamic tariff in the German compared to the Japanese survey (two-sided t-test: p-value = 0.026; two-sided Mann-Whitney Wilcoxon (MWW): p-value = 0.049).

As discussed in Section 3.4, we use probit and Tobit regression models to investigate the general preferences for dynamic electricity tariffs in detail. The corresponding estimation

[5] In line with Buryk et al. (2015), we use the potential savings associated to dynamic tariffs as the cost attribute. Since this attribute does not represent costs but savings, the ratio between any non-financial and the financial attribute represent the WTA a certain marginal or discrete change instead of the willingness to pay for it (e.g. Grutters et al., 2008).

Table 5: Descriptive statistics of dependent variables

		Germany		Japan	
		Baseline (a) (N = 516)	Treatment (b) (N = 543)	Baseline (c) (N = 1348)	Treatment (d) (N = 1334)
Frequency	Mean	4.256	4.416^{dd}	4.218	4.162^{bb}
	S.D.	(2.290)	(2.174)	(2.258)	(2.280)
Always	Mean	0.500	0.510	0.488	0.477
	S.D.	(0.500)	(0.500)	(0.500)	(0.500)
Never	Mean	0.155	0.142	0.148	0.160
	S.D.	(0.362)	(0.349)	(0.356)	(0.366)

Note: The superscript letters indicate statistically significant differences between the corresponding groups (a, b, c, and d) and the levels of significance: ^{a} < 0.10, ^{aa} < 0.05, ^{aaa} < 0.01. We use two-sided Fisher's exact tests to compare the binary variables 'Always' and 'Never' and two-sided Mann-Whitney Wilcoxon (MWW) rank-sum tests as well as two-sided t-tests to compare variable 'Frequency' across countries and treatments.

results are presented in Table 6. Given the coding structure, the first half of the estimated parameters correspond solely to the German sample, whereas the estimated parameters that correspond to the interaction terms represent the additional effect of the Japanese sample over the German sample.

With respect to the environmental treatment, we find neither a statistically significant effect on the likelihood to either 'always' or 'never' choose a dynamic tariff, nor a significant effect on the frequency in which respondents choose a dynamic tariff. However, having stronger environmental attitudes, i.e., a higher NEP score, is associated with a higher likelihood to 'always' choose a dynamic electricity tariff along with a higher frequency, in which respondents choose a dynamic electricity tariff. In addition, respondents considered trusting, risk seeking, and patient are associated with a significantly higher frequency of choosing a dynamic tariff. For patient and trusting respondents, these effects also hold for the likelihood of always choosing dynamic electricity tariffs.

Besides, we control for sociodemographic and household-specific characteristics. Surprisingly, none of the variables that approximate overall electricity consumption, i.e., income, electrical heating, household size, and number of children, appear to affect the outcome variables, except for the average time at home. In line with Yoshida et al. (2017), respondents who either themselves or whose household members spent on average more time at home are more likely to avoid dynamic tariffs. Furthermore, we find that an increase in a respondent's age by one year is associated with an increase in the likelihood of never choosing a dynamic tariff by 0.2 percentage points. Surprisingly, being married is associated with a

Table 6: Estimation results - determinants of choice frequencies

	Always		Never		Frequency	
Treatment	-0.003	(-0.112)	-0.017	(-0.780)	0.233	(0.627)
Environmental attitudes	0.021**	(2.137)	-0.007	(-0.989)	0.258**	(2.205)
Trusting	0.032*	(1.913)	-0.023*	(-1.883)	0.490**	(2.349)
Risk seeking	0.050	(1.450)	-0.040	(-1.541)	0.732*	(1.730)
Generous	0.030	(0.875)	-0.031	(-1.315)	0.464	(1.122)
Patient	0.074**	(2.290)	-0.009	(-0.421)	0.760**	(1.968)
Age	0.001	(0.619)	0.002**	(2.300)	-0.013	(-1.035)
Female	-0.035	(-1.127)	-0.016	(-0.745)	-0.201	(-0.529)
Household income[a]	-0.001	(-0.038)	0.009	(0.907)	-0.138	(-0.743)
University degree	-0.004	(-0.103)	-0.012	(-0.373)	0.008	(0.014)
Married	0.073**	(2.065)	-0.044*	(-1.724)	1.039**	(2.379)
Household size	-0.010	(-0.519)	-0.003	(-0.211)	-0.027	(-0.121)
No. of children	0.035	(1.087)	-0.029	(-1.155)	0.515	(1.420)
Average time at home	-0.003	(-1.335)	0.004*	(1.944)	-0.063*	(-1.940)
Electric Heating	-0.026	(-0.548)	-0.024	(-0.648)	-0.056	(-0.102)
10-years tariff change	-0.031	(-0.990)	-0.028	(-1.263)	-0.051	(-0.131)
Japan × Treatment	-0.002	(-0.065)	0.030	(1.156)	-0.353	(-0.814)
Japan × Environmental attitudes	-0.017	(-1.477)	0.001	(0.092)	-0.163	(-1.221)
Japan × Trusting	-0.034	(-1.619)	0.014	(0.884)	-0.434*	(-1.646)
Japan × Risk seeking	0.010	(0.239)	-0.014	(-0.436)	0.212	(0.399)
Japan × Patient	-0.050	(-1.285)	-0.004	(-0.151)	-0.439	(-0.950)
Japan × Generous	-0.009	(-0.216)	0.010	(0.362)	-0.100	(-0.206)
Japan × Age	-0.001	(-0.619)	0.000	(0.273)	-0.008	(-0.581)
Japan × Female	0.010	(0.259)	-0.006	(-0.240)	0.217	(0.484)
Japan × Household income[a]	0.007	(0.473)	-0.012	(-1.177)	0.227	(1.193)
Japan × University degree	0.021	(0.432)	-0.036	(-1.022)	0.489	(0.820)
Japan × Married	-0.049	(-1.138)	0.040	(1.324)	-0.870*	(-1.663)
Japan × Household size	0.016	(0.744)	0.010	(0.682)	0.048	(0.194)
Japan × No. of children	0.010	(0.266)	-0.018	(-0.625)	0.223	(0.529)
Japan × Average time at home	0.004	(1.298)	-0.003	(-1.102)	0.052	(1.340)
Japan × 10-years tariff change	0.025	(0.654)	0.028	(1.046)	0.011	(0.024)
Japan × Electric Heating	0.043	(0.837)	0.015	(0.389)	0.207	(0.347)
Respondents	3741		3741		3741	

Note: [a]Weighted household income in 1.000 Euro. The table shows discrete and marginal effects of probit and tobit estimation results with robust standard errors. Z-statistics in parenthesis. Levels of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

higher frequency of choosing a dynamic tariff as well as a higher probability to always and a lower probability to never do so, respectively.

Based on the included interaction terms, we reveal no significant differences between the two countries. This is particularly interesting with respect to the treatment variable and the measure of environmental attitudes. The only exceptions are the weakly significant reductions in the higher frequency in which married respondents and respondents with a higher trust level choose a dynamic tariff.

In general, our results indicate that environmental attitudes, marital status as well as economic preferences are important determinants of households' general tariff choices. However, the fact that none of the variables approximating electricity consumption behaviour along with further technical household characteristics significantly affect these features, could be an indication that the diffusion of dynamic tariffs does not need to be limited to specific customer types.

4.2. Preferences for dynamic electricity tariffs

As discussed in Section 3.4, we conduct a 2×2-split sample analysis to address our central research questions. Correspondingly, Table 7 reports the country-specific estimation results based on mixed logit models for the baseline and the treatment group. We use the Stata command 'mixlogit', written by Hole (2007b), to conduct the simulated maximum likelihood estimation of the mixed logit models based on 10,000 Halton draws.

The two attributes '*potential savings*' and '*necessary shift of consumption*' are included as continuous variables. For all remaining attributes that are on ordinal scales, we use n-1 binary variables to assess respondents' preferences for the corresponding attribute levels. The estimated standard deviations indicate significant heterogeneity in respondents preferences for the different tariff characteristics.

As the treatment text explicitly addressed the two tariff characteristics '*number of time zones*' and '*price update*', which in addition largely determine the economic efficiency of a dynamic tariff, we describe the corresponding results in detail. With respect to the former attribute, the baseline level is '2 time zones'. It is striking, that for the Japanese sample, none of the other levels (i.e., 4, 12, and 24 time zones) significantly alters the likelihood of choice of a dynamic tariff. For the German sample, we observe a similar – but less pronounced – tendency. In fact, only the estimated negative coefficients for the '24 time zones' are statistically significant at the 1% level. This negative coefficient implies that respondents' likelihood of choosing a dynamic tariff decreases significantly if prices change hourly instead of twice daily.

Table 7: Estimation results - preferences for dynamic electricity tariffs

	Germany				Japan			
	Baseline		Treatment		Baseline		Treatment	
Mean								
4 time zones	-0.035	(-0.434)	-0.146*	(-1.872)	0.033	(0.516)	0.065	(1.033)
12 time zones	-0.061	(-0.737)	-0.118	(-1.414)	-0.115	(-1.297)	-0.024	(-0.273)
24 time zones	-0.292***	(-3.095)	-0.272***	(-3.421)	-0.054	(-1.038)	-0.085	(-1.586)
Daily price update	-0.715***	(-6.553)	-0.727***	(-6.359)	-0.182***	(-2.966)	-0.124**	(-2.004)
Weekly price update	-0.652***	(-6.126)	-0.428***	(-4.211)	0.008	(0.109)	0.166**	(2.521)
Monthly price update	-0.194**	(-2.259)	-0.046	(-0.535)	0.337***	(4.640)	0.464***	(6.380)
Potential savings	0.055***	(6.626)	0.068***	(7.612)	0.049***	(8.445)	0.049***	(8.425)
Shift of consumption	-0.062***	(-7.334)	-0.066***	(-6.835)	-0.030***	(-7.410)	-0.034***	(-8.104)
5 percent cost cap	0.438***	(4.188)	0.518***	(5.024)	0.504***	(7.509)	0.550***	(7.982)
10 percent cost cap	0.298***	(3.516)	0.220**	(2.399)	0.224***	(3.640)	0.280***	(4.407)
15 percent cost cap	0.017	(0.180)	-0.033	(-0.324)	-0.297***	(-4.076)	-0.240***	(-3.382)
Data analysis	-0.142**	(-2.075)	-0.192**	(-2.507)	0.039	(0.726)	0.024	(0.426)
& 3rd parties	-1.126***	(-9.299)	-1.116***	(-9.034)	-0.826***	(-10.582)	-0.727***	(-9.348)
ASC (Tariff 1)	-0.060	(-0.835)	0.080	(1.119)	-0.213***	(-3.282)	-0.094	(-1.484)
ASC (Tariff 2)	-0.092	(-1.220)	0.060	(0.856)	0.007	(0.146)	0.024	(0.497)
Standard deviation								
4 time zones	0.375	(1.576)	-0.161	(-0.430)	0.995***	(9.226)	0.883***	(7.988)
12 time zones	0.405*	(1.716)	0.293	(0.986)	-0.995***	(-5.033)	1.024***	(5.337)
24 time zones	0.807***	(4.819)	-0.001	(-0.010)	-0.472***	(-4.184)	0.739***	(8.385)
Daily price update	0.974***	(6.483)	1.129***	(7.282)	0.587***	(5.040)	0.612***	(5.106)
Weekly price update	0.829***	(5.730)	0.946***	(6.145)	-0.678***	(-5.790)	-0.249	(-1.180)
Monthly price update	0.672***	(4.106)	0.784***	(5.233)	1.049***	(10.278)	1.043***	(10.173)
Shift of consumption	0.106***	(7.969)	0.140***	(11.140)	0.078***	(13.049)	0.085***	(14.074)
5 percent cost cap	0.679***	(4.291)	0.561***	(2.886)	0.841***	(9.215)	0.886***	(9.947)
10 percent cost cap	-0.016	(-0.967)	0.628***	(5.125)	-0.386***	(-2.976)	-0.375**	(-2.273)
15 percent cost cap	0.060	(0.523)	0.665***	(3.739)	0.962***	(9.154)	0.755***	(6.328)
Data analysis	0.423***	(2.779)	0.787***	(7.318)	0.731***	(7.807)	0.834***	(9.196)
& 3rd parties	1.099***	(7.912)	1.092***	(8.003)	1.429***	(14.113)	1.533***	(15.716)
ASC (Tariff 1)	0.798***	(6.731)	0.701***	(5.479)	1.129***	(12.726)	1.048***	(12.823)
ASC (Tariff 2)	0.837***	(7.370)	0.462***	(3.035)	-0.507***	(-5.146)	0.506***	(5.021)
Observations (respondents)	3096 (516)		3258 (543)		8088 (1348)		8004 (1334)	

Note: All models are estimated with robust standard errors. Z-statistics in parenthesis. Levels of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The baseline level for the attribute price update is 'yearly'. For this attribute, a country difference is immediately noticeable. While for the German sample all estimated parameters are negative, Japanese respondents prefer monthly over annual price changes. With respect to the treatment, this also holds true for weekly price updates. Japanese respondents only experience disutility if prices are updated daily. In the case of the German sample, only in the treatment group is the estimated parameter for 'monthly' insignificant. Apart from that, we can see a clear decline in preferences from annual to daily price adjustments.

Intuitively, the estimated mean parameter for the attribute '*potential savings*' is positive and statistically significantly different from zero at the 1% level across all groups. This implies that greater potential savings increase the likelihood of choice of a dynamic tariff. Similarly, the mean estimated parameter for the attribute '*necessary shift of consumption*' is statistically negative at the 1% level for all four groups, which implies that greater required load shifts reduce the likelihood that respondents chose a particular tariff.

Across both countries, we detect preferences to be guarded from economic risks, i.e., respondents prefer 5 % or 10 % price caps over no price caps (base level). However, the estimated parameter that corresponds to the 15 % level is insignificant in both German groups and even significantly negative in the Japanese sample. Furthermore, German respondents are less likely to choose a tariff that allows tariff providers and grid operators to analyse households' consumption data. Across all four groups, the choice probability for a tariff significantly decreases, if consumption data are additionally shared with third parties.

4.3. Willingness to accept dynamic electricity tariffs

To put the results discussed in Section 4.2 into perspective, we estimate the corresponding WTA values as described in Section 3.4. To this end, Table 8 follows the 2×2 design and reports the estimated mean WTA values for all attributes or their levels. We use the command 'wtp', written by Arne R. Hole and discussed in Hole (2007a), to estimate the mean marginal WTA.

Furthermore, Figure 1 and Figure 2 illustrate the WTA values by treatment and country for the indicated attributes or attribute levels, respectively. In both figures, the error bars indicate the 95 % confidence intervals and the displayed p-values refer to the complete combinatorial test proposed by Poe et al. (2005). Only significant test results are displayed. Significant WTA values are shown in blue, whereas insignificant values, which we do not report in Table 8, are displayed in light blue.

The three panels in the first row of Figure 1 correspond to the *number of time zones*. Intuitively, the insignificant estimated mean parameters reported in Table 7 translate into

Table 8: Mean WTA estimates by country and treatment

	Germany				Japan			
	Baseline		Treatment		Baseline		Treatment	
4 Time zones	n.s.	–	2.25	[0.06;4.75]	n.s.	–	n.s.	–
12 Time zones	n.s.	–	n.s.	–	n.s.	–	n.s.	–
24 Time zones	5.43	[1.76;9.72]	3.96	[1.48;6.84]	n.s.	–	n.s.	–
Daily	12.93	[8.52;19.67]	10.69	[7.18;15.71]	3.58	[1.27;6.39]	2.31	[0.03;4.95]
Weekly	11.90	[7.66;18.45]	6.23	[3.35;10.04]	n.s.	–	-3.53	[-6.40;-0.96]
Monthly	3.50	[0.52;7.35]	n.s.	–	-6.75	[-10.59;-3.81]	-9.53	[-14.12;-6.34]
Necessary shift	1.12	[0.78;1.67]	0.99	[0.69;1.42]	0.61	[0.42;0.88]	0.69	[0.48;0.99]
5 % cost cap	-8.08	[-13.30;-4.51]	-7.43	[-11.57;-4.53]	-10.28	[-14.30;-7.47]	-11.19	[-15.33;-8.32]
10 % cost cap	-5.49	[-9.39;-2.46]	-3.20	[-6.37;-0.60]	-4.67	[-7.46;-2.24]	-5.46	[-8.38;-2.94]
15 % cost cap	n.s.	–	n.s.	–	5.93	[2.87;9.49]	4.78	[1.85;8.14]
Data analysis	2.68	[0.24;5.56]	2.89	[0.73;5.52]	n.s.	–	n.s.	–
& 3rd parties	20.30	[14.61;29.52]	16.43	[12.13;22.78]	16.26	[12.36;21.70]	14.44	[10.82;19.41]

Notes: WTA values express the additional potential savings (in %) that households require to accept a certain attribute or the corresponding attribute level. Negative values thus correspond to potential savings that respondents are willing to dispense. 95 % confidence intervals in parenthesis.

insignificant WTA values. Only when prices change hourly, we observe highly significant aversion in the German sample. In fact, German respondents require on average approximately 5.4 % additional potential savings (4.0 % in the treatment group) to accept 24 time zones (compared with 2 time zones), which is statistically significantly more compared to the Japanese respondents. In both surveys we observe no significant variations across the two treatment groups, which is likely due to the high share of insignificant estimated mean parameters corresponding to the attribute levels.

Intuitively, a larger number of time zones per day will improve a tariffs capability to reflect the short-run social marginal costs of electricity generation and thereby increase the overall economic welfare associated with the adoption of such tariff (Borenstein and Bushnell, 2018). Our finding, that a higher number of time zones does not increase households participation costs associated to dynamic pricing, which is in line with the results of Wolak (2011), therefore marks a highly relevant implication for efficient tariff designs.

With respect to the second attribute (*price update*), we find that the average WTA values for daily, weekly, or monthly price updates are significantly higher in the German than in the Japanese samples (second row of Figure 1). Differences in country-specific defaults might

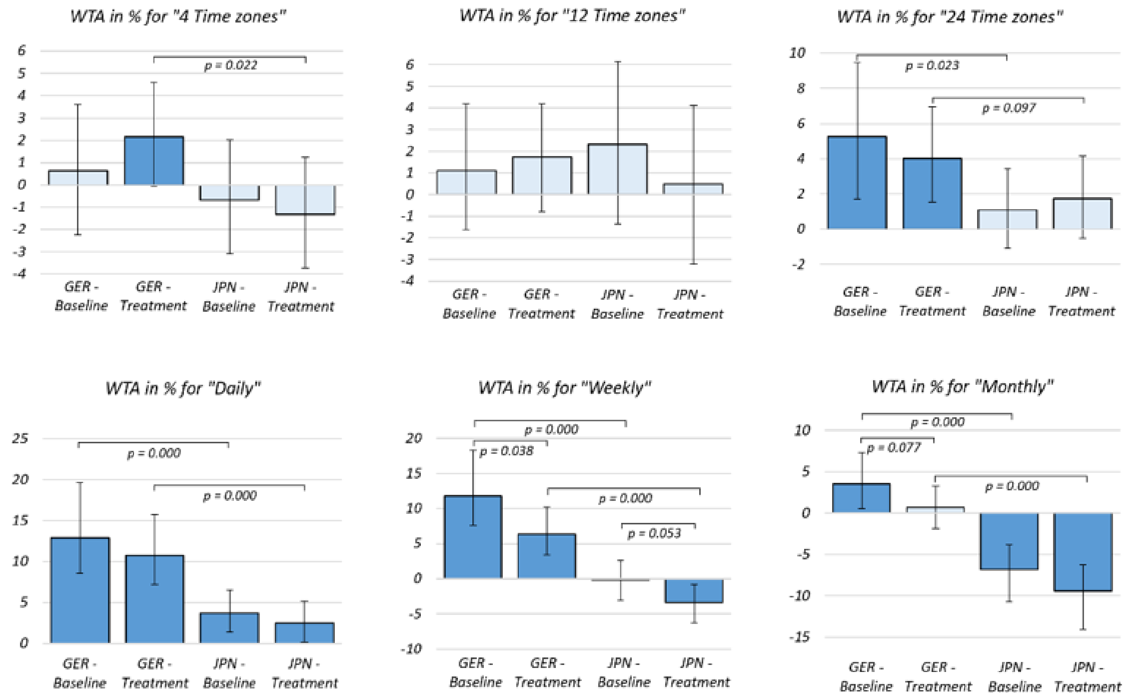


Figure 1: Estimated WTA in % for the number of time zones and price updates by country and treatment

be a potential explanation for this differential. While 93 % of respondents from Germany indicated that their current tariff is updated yearly or even less frequent, monthly price updates are the default in Japan[6].

Furthermore, in line with Buryk et al. (2015) and Kowalska-Pyzalska et al. (2014), we find that additional knowledge of the environmental benefits associated with dynamic tariffs significantly reduces household aversion to the frequency of price updates. When German households receive information on the environmental benefits of dynamic tariffs, increasing the frequency of price updates to monthly comes at zero additional participation costs, which is significantly different from the baseline group. In addition, the treatment significantly reduced Germans' aversion against weekly price updates. Similarly, the treatment significantly increased respondents preferences towards weekly price updates, with respect to the Japanese sample. In fact, for the Japanese treatment group we see that households even prefer weekly price updates over annual prices.

[6]For example TEPCO, one of Japans major electricity retailer, passes on changes in fuel costs to their customers on a monthly basis: https://www.tepco.co.jp/en/ep/rates/electricbill-e.html (last accessed 15.03.2022).

In sum, this findings comprise another step towards unlocking the efficiency potential of dynamic tariffs, as monthly instead of yearly price updates are already able to capture a significant share of the economic efficiency gains associated with RTP tariffs (Holland and Mansur, 2006).

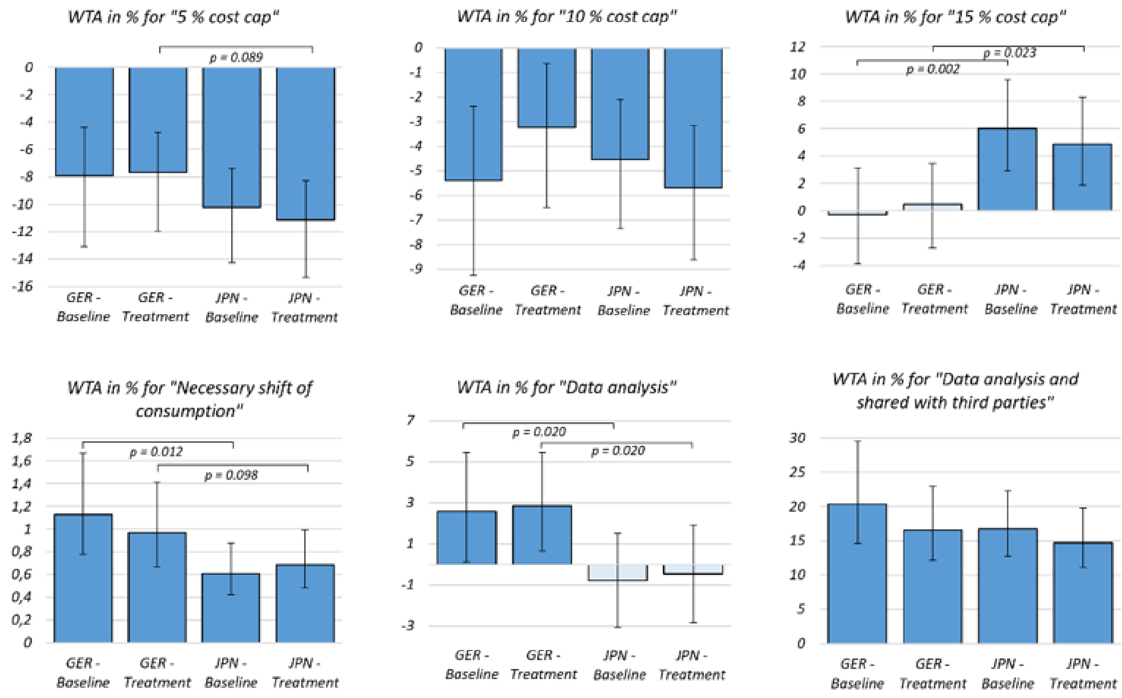


Figure 2: Estimated WTA in % for a cap for additional costs, necessary shifts of consumption and data utilization by country and treatment

We also find differences across the two samples with respect to respondents preferences for a cap for additional costs (first row of Figure 2). Japanese respondents are willing to accept roughly 10.3 % lower potential savings (11.2 % in the treatment group), if a tariff is equipped with a 5 % cost cap instead of having ‘No cost cap’ (base level). By contrast, German respondents are only willing to accept 8.1 % (7.4 % in the treatment group) fewer potential savings. With respect to the treatment group, this difference is statistically significant at the 10 % level. Surprisingly, respondents from Japan prefer a tariff without a cost cap over a tariff with a 15 % cost cap, whereas German respondents are indifferent with respect to the two attribute levels.

By implication, the WTA lower potential savings in order to be ensured against additional costs suggests that respondents fear facing increased electricity costs in case they fail to shift their electricity consumption. However, following economic theory, households will not counter-intuitively shift electricity consumption into time zones with high electricity prices.

Therefore, in theory, their costs will never reach the price caps. Consequently, such caps should not provoke a reduction in economic efficiency. Since we find caps for additional costs to significantly reduce households aversions against dynamic tariffs, which is in line with the findings of Schlereth et al. (2018), they constitute a straightforward and cost-efficient tool to increase households' preferences for dynamic tariffs.

The first panel in the second row of Figure 2 displays the average additional potential savings that households require to accept the necessity to additionally shift 1 % of their electricity consumption in order to realize the savings. For both treatments, the higher bars for the German sample indicate that Germans need significantly higher potential financial compensation in order to respond to the price signals. However, this difference becomes less pronounced when respondents receive the environmental information treatment.

Furthermore, our results support the findings of Richter and Pollitt (2018) and Pepermans (2014) that households hold strong aversions to their consumption data being shared with third parties (displayed in the fifth and sixth panel of Figure 2). Even though tariff providers or grid operators might see this as an additional source of income, we expect household demands for potential financial compensation of at least 15 % to cause total revenue to suffer. In fact, German respondents do not even want their provider to analyse their consumption data, as they require additional potential savings of approximately 2.7 % (2.9 % in the treatment group), to accept such a tariff. Country differences could also relate to different conditions in the two countries. Technically, 'data analysis' is the default in Japan. By contrast, only 1.3 % of our German respondents (half of those already with smart meters installed) indicated that their electricity provider would analyse their consumption data. Therefore, on average, German respondents would experience a loss in privacy when their provider analyses their consumption data, whereas Japanese respondents do not appear to care as much about the utilisation of their data unless they are shared with third parties.

Finally, based on the discussed findings we believe a TOU tariff, which is characterised by 12 price zones (or even 24), monthly price updates (or even weekly), a 5 % price cap, and restrictive use of consumption data, to be suitable to increase economic efficiency while accounting for households' participation costs. Furthermore, when the environmental benefits associated with such tariffs are highlighted, they incorporate significantly less transaction costs for households while capturing a significant share of the total economic efficiency associated with RTP tariffs. Therefore, such information is a promising addition to overcome households' acceptance barriers.

Nevertheless, we must also discuss some limitations of our study before drawing our final conclusions in Section 5. In particular, despite asking our respondents to assume that smart meters were installed in their household without any additional costs, we cannot rule out that the higher aversion against dynamic electricity tariffs we find among the German sample is (at least partially) driven by their negative preferences for the installation of smart meters (and the associated costs).

Furthermore, we must also acknowledge that our SCE focuses solely on the volumetric cost component of residential electricity prices and not on fixed fees, which typically are also part of residential tariffs. In particular, Borenstein (2016) argues that such two-part tariffs, i.e., tariffs that constitute a fixed fee (e.g., per month) and dynamic unit charges (e.g., per kWh), are most suitable for optimising the economic efficiency of residential rates.[7] The implications of our analysis are thus limited to the volumetric part of residential prices, which is naturally also the only part eligible for dynamic pricing.

5. Conclusion

We conducted two representative household surveys in Germany and Japan to examine preferences and acceptance barriers towards dynamic electricity tariffs. To this end, our unique experimental design allows to disentangle preferences for inter- and intraday price changes, which are two central determinants of the economic efficiency associated with dynamic tariffs. On the one hand, our results suggest that households in Germany and Japan require significant compensation to accept frequently changing price patterns. A tendency that is significantly stronger in the German sample, indicating that Japanese households are more willing to accept dynamic electricity tariffs. On the other hand, we find that our respondents do not mind several price changes during a day, except for German households' disapproval of hourly prices.

Our findings suggest that if price patterns are known for a longer period, respondents do not mind TOU tariffs with several price zones per day. Such TOU tariffs not only more efficiently reflect the short-run social marginal costs of electricity generation than day-and-night tariffs, but, in particular in combination with cost caps and a restrictive utilisation of consumption data, also seem capable of reducing households' adoption barriers and thereby

[7] In theory, prices are efficient if they reflect the short-run social marginal costs of electricity production. However, in RTP tariffs several factors, including the (negative) externalities of electricity production, the need for utilities to cover high fixed costs, and the exploitation of market power, act against dynamic pricing being economically efficient (Borenstein, 2016). Therefore, Borenstein (2016) argues that two-part tariffs are the 'least bad' efficient solution to this problem.

increasing the likelihood that they take-up dynamic tariffs, which is essential to unlock (at least some of) the benefits associated with dynamic electricity pricing.

Furthermore, environmental information can help to decrease aversions towards more frequent price changes, which could further promote dynamic electricity tariffs. Given providing additional information is typically inexpensive, this can be a highly cost-effective policy mechanism for increasing household preferences towards dynamic electricity tariffs.

To this end, further research should focus on additional instruments, e.g., the visual display of saved CO_2 emissions, to help overcome prevailing household acceptance barriers. In addition, we believe that the incorporation of household WTA dynamic tariffs in general – or single tariff characteristics in particular – into the economic efficiency assessment of such tariffs would be a suitable approach for taking household participation costs into account. In this respect, the fact that household preferences for dynamic tariffs are unaffected by a larger number of price zones each day seems a promising finding to realise efficiency gains. In fact, the quantification of such efficiency gains, particularly in the context of two-part tariffs and distributional effects, is already a promising research objective.

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Appendix A. Additional figures and tables

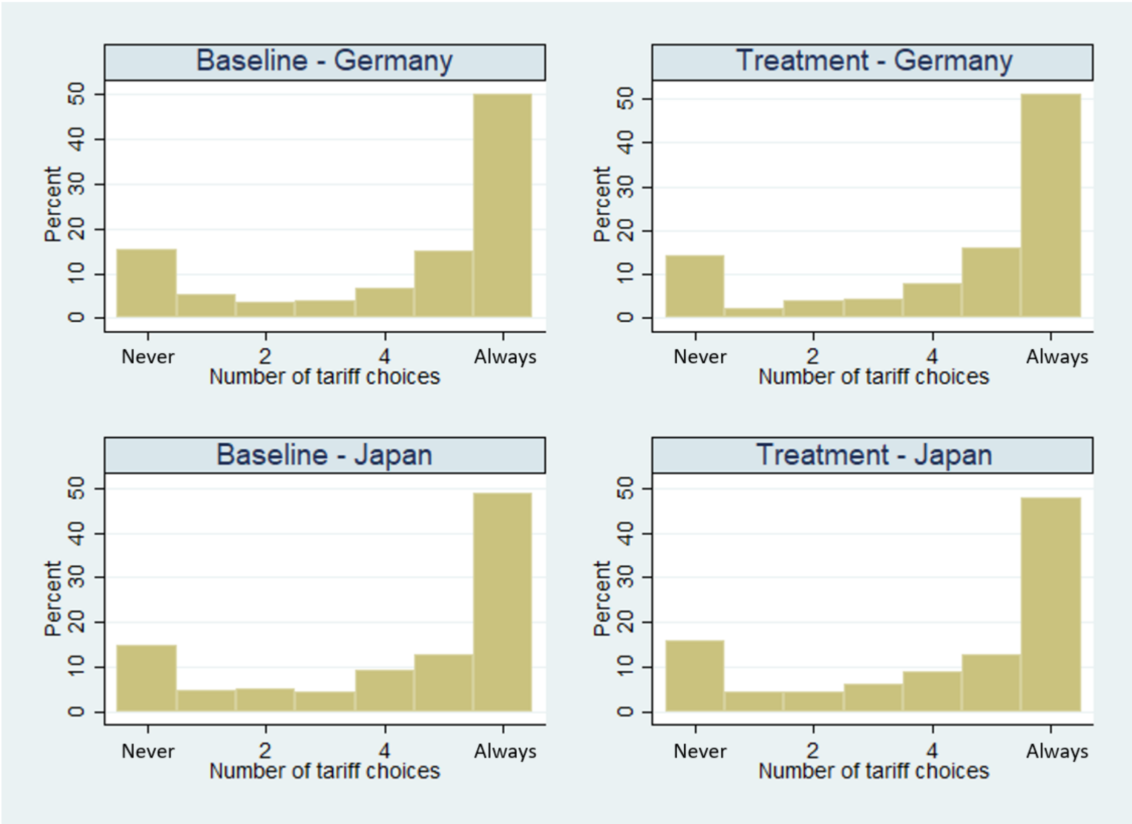

Figure A.1: Frequency of tariff choices

Table A.1: Baseline group: summary statistics by country

	Germany				Japan				
	Count	Mean	SD	Min-Max	Count	Mean	SD	Min-Max	P-value
Environmental attitudes	516	4.76	1.49	0-6	1348	3.73	1.86	0-6	0.000
Trusting	516	0.87	0.94	0-3	1348	0.52	0.75	0-3	0.000
Risk seeking	516	0.34	0.48	0-1	1348	0.16	0.37	0-1	0.000
Generous	516	0.67	0.47	0-1	1348	0.48	0.50	0-1	0.000
Patient	516	0.56	0.50	0-1	1348	0.54	0.50	0-1	0.404
Age	516	50.17	16.79	18-85	1348	45.56	13.53	20-69	0.000
Female	516	0.51	0.50	0-1	1348	0.51	0.50	0-1	0.784
Household income[a]	516	1.88	0.93	0.18-8.66	1348	3.95	2.74	0.34-15.39	0.000
University degree	516	0.17	0.38	0-1	1348	0.53	0.50	0-1	0.000
Married	516	0.49	0.50	0-1	1348	0.61	0.49	0-1	0.000
Household size	516	2.22	1.13	1-10	1348	2.70	1.29	1-10	0.000
No. of children	516	0.28	0.65	0-6	1348	0.33	0.73	0-5	0.416
Average time at home	516	17.66	6.28	2-24	1348	18.37	5.50	2-24	0.166
Electric Heating	516	0.12	0.32	0-1	1348	0.53	0.50	0-1	0.000
10-years tariff change	516	0.64	0.48	0-1	1348	0.32	0.47	0-1	0.000

Notes: [a]Weighted household income in 1.000 Euro. P-values in the last column refer to Pearson's chi-squared test for independence between the samples in case of binary variables and to the Kruskal-Wallis equality-of-populations rank test for non-binary variables.

Table A.2: Treatment group: summary statistics by country

	Germany				Japan				
	Count	Mean	SD	Min-Max	Count	Mean	SD	Min-Max	P-value
Environmental attitudes	543	4.80	1.54	0-6	1334	3.73	1.82	0-6	0.000
Trusting	543	0.87	0.97	0-3	1334	0.49	0.74	0-3	0.000
Risk seeking	543	0.31	0.46	0-1	1334	0.17	0.37	0-1	0.000
Generous	543	0.66	0.47	0-1	1334	0.47	0.50	0-1	0.000
Patient	543	0.56	0.50	0-1	1334	0.55	0.50	0-1	0.597
Age	543	49.94	16.20	18-91	1334	45.75	13.59	20-69	0.000
Female	543	0.47	0.50	0-1	1334	0.52	0.50	0-1	0.034
Household income[a]	543	1.98	1.27	0.13-15.00	1334	4.07	2.88	0.34-15.39	0.000
University degree	543	0.14	0.35	0-1	1334	0.53	0.50	0-1	0.000
Married	543	0.49	0.50	0-1	1334	0.59	0.49	0-1	0.000
Household size	543	2.22	1.18	0-9	1334	2.61	1.28	0-8	0.000
No. of children	543	0.29	0.70	0-5	1334	0.32	0.71	0-4	0.191
Average time at home	543	18.09	5.84	2-24	1334	18.27	5.72	2-24	0.940
Electric Heating	543	0.12	0.33	0-1	1334	0.52	0.50	0-1	0.000
10-years tariff change	543	0.63	0.48	0-1	1334	0.33	0.47	0-1	0.000

Notes: [a]Weighted household income in 1.000 Euro. P-values in the last column refer to Pearson's chi-squared test for independence between samples in case of binary variables and to the Kruskal-Wallis equality-of-populations rank test for non-binary variables.