

# **Essays on Energy Economics and Consumer Preferences**

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Diplom-Volkswirtin  
Swantje Brigitte Sundt  
aus Stuttgart

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Erstbegutachtung: Prof. Dr. Katrin Rehdanz  
Zweitbegutachtung: Prof. Dr. Dr. Ulrich Schmidt

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## Contents

List of Abbreviations.....	IV
List of Tables.....	VI
List of Figures .....	VII
1 Introduction .....	1
References .....	12
2 First Paper: Consumers' willingness to pay for green electricity: A meta-analysis of the literature .....	16
2.1 Introduction .....	17
2.2 Overview of the willingness-to-pay for renewable energy literature.....	18
2.3 Description of data .....	19
2.4 Meta-analysis and value transfer.....	24
2.4.1 Meta-regression model.....	24
2.4.2 Quality of value transfer.....	26
2.5 Results .....	28
2.5.1 Meta-regression.....	28
2.5.2 Value Transfer.....	31
2.6 Discussion/Conclusions .....	34
References .....	36
3 Second Paper: Consumers' Willingness to Accept Time-of-Use Tariffs for Shifting Electricity Demand .....	41
3.1 Introduction .....	42
3.2 Literature Review .....	43
3.3 Methodology and Data .....	46
3.3.1 Design of the Choice Experiment .....	46
3.3.2 Questionnaire and Choice Set Design.....	48

3.3.3	Econometric Approach.....	49
3.3.4	Identifying Decision Strategies across Respondent Groups.....	51
3.4	Results .....	52
3.4.1	Descriptive Results.....	52
3.4.2	Estimation Results.....	53
3.4.3	Decision Strategies across Respondent Groups .....	55
3.5	Scenario Analysis .....	60
3.6	Discussion and Conclusions.....	62
3.A	Appendix .....	64
	References .....	65
4	Third Paper: Influence of Attitudes on Willingness to Choose Time-of-Use Electricity Tariffs in Germany. Evidence from Factor Analysis .....	68
4.1	Introduction .....	69
4.2	Literature Review .....	70
4.3	Methodology and Data .....	72
4.3.1	Theoretical Background .....	72
4.3.2	Econometric approach.....	74
4.3.3	Survey Design .....	76
4.4	Results .....	77
4.4.1	Descriptive Sample Statistics .....	77
4.4.2	Empirical Analysis .....	81
4.4.2.1	Results of the Factor Analysis.....	81
4.4.2.2	Results of the Regression Analysis .....	83
4.5	Discussion .....	85
4.6	Conclusion.....	87
4.A	Appendix A .....	90

4.B	Appendix B .....	90
	References .....	98
	Erklärungen .....	103

## List of Abbreviations

ACER	The European Union Agency for the Cooperation of Energy Regulators
AIC	Akaike's Information Criteria
BIC	Bayesian Information Criteria
CE	choice experiment
CEER	The Council of European Energy Regulators
CL	conditional logit
CPP	critical peak price
CV	contingent valuation
CO <sub>2</sub>	carbon dioxide
DSM	Demand side management
IEA	International Energy Agency
ILP	individual level parameter
IRENA	International Renewable Energy Agency
IPCC	Intergovernmental Panel on Climate Change
Gt	giga tons
kW	kilowatt
kWh	kilowatt hour(s)
ln	natural logarithm
MAPE	mean absolute percentage error
mio	million
MSE	mean squared error
MWh	megawatt hour

MXL	mixed logit
NEP	New Environmental Paradigm
NIMBY	not in my backyard
OECD	The Organisation for Economic Co-operation and Development
PT	peak time
RE	renewable energy
Std.dev.	standard deviation
TPB	Theory of Planned Behavior
TOU	time-of-use
VBN	Value-Belief norm
WTA	willingness to accept
WTP	willingness to pay



## List of Tables

Table 2.1: Studies Included in the Meta-Regression.....	20
Table 2.2: Explanatory Variables in Meta-Regression .....	24
Table 2.3: Results of Meta-Regression by Model.....	29
Table 2.4: Marginal Effects on WTP - Model 1 with Interactions .....	30
Table 2.5: Quality of Value Transfer .....	32
Table 3.1 Attributes, their description, and their levels .....	48
Table 3.2 Descriptive Statistics .....	52
Table 3.3 Appliance Ownership/Times of high Electricity Consumption .....	53
Table 3.4 Estimation of Choice Experiment .....	54
Table 3.5 Unconditional WTA in € based on MXL Results.....	55
Table 3.6 Median of marginal conditional WTA in € (in brackets: [5%-quantile, 95%-quantile]) .....	58
Table 3.7 Data used to estimate shifts in electricity demand. ....	61
Table 3.8 Potential shift in electricity demand by scenarios.....	61
Table 4.1: Sociodemographic Characteristics .....	78
Table 4.2: Characteristics of Current Electricity Tariff .....	78
Table 4.3: Statements Measuring Motivation and Social Norms.....	79
Table 4.4: Perceived Impacts of TOU tariffs with Prices Related to Electricity Demand and Supply .....	80
Table 4.5: Feasibility of Electricity Saving Measures .....	80
Table 4.6: Climate Change Awareness .....	81
Table 4.7: Rotated Factors .....	82
Table 4.8: Ordered Logit Models to Predict Willingness to Choose a TOU Tariff .....	84
Table 4.9 Results unrotated factor analysis.....	90

**List of Figures**

Figure 2.1: Number of Published Studies by Year and Continent ..... 19

Figure 2.2: Mean WTP by Country..... 21

Figure 2.3: Mean WTP by Continent ..... 22

Figure 2.4: Value Transfer Full Sample ..... 32

Figure 2.5: Value Transfer for Restricted Sample ..... 33

Figure 3.1 Translated Choice Set. Tariff 3 was introduced as Status Quo ..... 49

Figure 3.2 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. .... 57

Figure 3.3 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..... 59

Figure 4.1: Willingness to Choose TOU tariffs ..... 85

# 1 Introduction

Anthropogenic climate change poses the major challenge of the 21<sup>st</sup> century. Indeed, human-induced climate change has triggered extreme weather events across the globe, according to the latest Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2021). Global warming has been similarly affected. The cause of global warming is greenhouse gas emissions, where carbon dioxide (CO<sub>2</sub>) emissions are responsible for the largest share in the temperature increase. Irrespective of the emissions scenario, the global temperature is set to increase until mid-21<sup>st</sup> century, resulting in a temperature increase of between 1.5°C and 2°C. Importantly, the point of comparison for this prognosis is the period 1850 to 1900. Unless emissions are drastically reduced i.e. slashed to zero net CO<sub>2</sub>-emissions (IPCC, 2021), this adverse outcome is highly likely.

The energy sector is the largest contributor to CO<sub>2</sub>-emissions. In 2019, fossil CO<sub>2</sub>-emissions exceeded 38 Gt (Crippa et al., 2020) of which 33.2 Gt were emitted by the energy sector (IEA, 2020). Of these energy-related CO<sub>2</sub>-emissions, almost half relate to emissions from coal combustion alone. Although in 2020, energy-related emissions dropped to 31.5Gt CO<sub>2</sub>, due to the COVID-19 pandemic, the International Energy Agency (IEA) expects this effect to rebound. In value terms, the rebound effect is estimated at 4.8 percent for 2021 (IEA, 2021). Simultaneous to the rebound effect, energy demand is expected to increase by 4.6 percent in 2021 (IEA, 2021). Accordingly, it would be naïve to think that the energy sector can be fully decarbonized without an increase in the ratio of renewable energy (RE) to overall energy. Specifically, this will mean boosting the share of RE from its relatively low 2018 starting point, namely 14 percent of global primary energy supply (IRENA, International Renewable Energy Agency, 2021).

Given the critical role to be played by RE, it is unsurprising that governments have ratified ambitious expansion targets for this energy source. To illustrate, Germany has approved an increase to 65 percent by 2030, in the share of RE in gross electricity consumption (Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2020). Policies relating to this goal, are expected to impact directly on electricity consumers. Feed-in tariffs represent a case in point – an instance where the RE goals are expected to carry consequences for consumers. The purpose of these tariffs, is to enable suppliers to more easily recover their investment costs, via increased electricity prices for consumers. To be economically efficient, these subsidies should be aligned to the consumers' willingness to pay (WTP). Only with this price-WTP alignment, can the tariffs induce an equivalent increase in the share of renewables within the electricity mix.

Researchers can elicit this WTP, using revealed or stated preference methods. *Revealed preference methods* imply observing the actual behavior of consumers. Alternatively, *stated preference methods* use hypothetical scenarios as a means of estimating WTP values (Boxall et al., 1996). Stated preference methods are preferred, in the case of estimating the WTP for RE (Chaikumbung, 2021). This might be due to the fact that on real markets the RE share in the electricity mix does not vary sufficiently to gather detailed information on WTP for an increasing share of RE in the electricity mix using revealed preference methods.

Specifically, when applying the stated preference method, there are two broad options for eliciting preferences – contingent valuation (CV) and choice experiments (CE). In CV studies, researchers describe a certain scenario for which respondents have to state how much they are willing to pay for this scenario. In a CE, respondents choose between different alternatives for which they have to pay a certain amount. Where an option exists to retain the status quo, respondents may choose to do so without incurring any additional costs. In this case, the WTP can be estimated by comparing the choice made by the respondent, to the status quo (Boxall et al., 1996).

Numerous studies have attempted to elicit the WTP for RE i.e., consumers price sensitivity towards RE. Probably, the first study of this kind relates to work by Farhat and Houston (1996) followed by a few studies in the early 2000s. Since 2007, this literature has increased exponentially (5 studies in 2007 compared to 1 to 2 studies per year in 2000-2006; Sundt and Rehdanz, 2015). This implosion in the literature is not matched by a consensus over the 'correct' WTP values. Instead, we witness a wide range of these values, each differing significantly. And still the research is ongoing (Danne et al., 2021). This lack of consensus in the literature over consumers' WTP for RE, calls for a systematic overview of these studies. Specifically, what is needed is a meta-regression, identifying the most influential factors in the WTP estimates. Accordingly, the first paper of this thesis provides the first<sup>1</sup> meta-regression analysis of the literature on consumers' WTP for green electricity (Sundt and Rehdanz, 2015, Chapter 2). In sum, this study sets out to answer the following question:

*Do we observe a significant WTP for an increasing share of RE in the electricity mix in previous studies, and how does study design influence WTP estimates?*

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<sup>1</sup> Even though the meta-analysis by Soon and Ahmad (2015) has been published online in January 2015 they already refer to our working paper published in 2014 (Sundt and Rehdanz 2014).

As of 2013, 48 studies have elicited the WTP for green electricity. However, only 18 appropriated themselves for inclusion into our meta-analysis "WTP for a higher RE share in the current electricity mix" (Sundt and Rehdanz, 2015, p. 2). In terms of research findings, we can reveal that public acceptance of RE is globally high. On the other hand, public acceptance towards biomass is inconclusive. Our meta-regression (weighted ordinary least squares) reveals that WTP per month for RE increases in a country's share of RE, but decreases in a country's share of hydropower. Additionally, WTP estimates are larger if a survey was conducted in the USA. A further finding is that estimates based on choice experiments exceed those based on contingent valuations. Finally, additional important drivers of WTP estimates are consumers' knowledge about RE, their household characteristics, income, and their level of education.

Following the publication of a working paper version of this study in 2014, several peer-reviewed meta-regressions on WTP for RE followed, i.e., Soon and Ahmad (2015), Bigerna and Polinori (2015), Ma et al. (2015), Grilli (2017), Chaikumbung (2021). In the case of the three studies published in 2015, the number of studies included in the meta-regression varies. While Bigerna and Polinori (2015) similarly considered 18 studies, Ma et al. (2015) and Soon and Ahmad (2015) considered 29 and 30 studies, respectively. These differences result from whether the researchers considered only WTP for RE in general or also considered WTP for specific RE sources. A further factor underpinning the differences in sample size was the decision to what extent one should adjust WTP values to guarantee their comparability. In later meta-regressions, the number of studies considered has increased to 34 (Grilli, 2017) and 91 (Chaikumbung, 2021), respectively.

Instead of presenting regression results for both possible dependent variables, i.e., WTP for RE per month and per kWh (Sundt and Rehdanz, 2015), later meta-regressions only present results for either WTP per month (Chaikumbung, 2021; Grilli, 2017; Soon and Ahmad, 2015) or WTP per kWh (Bigerna and Polinori, 2015; Ma et al., 2015). This makes it difficult to compare some results. For example, Sundt and Rehdanz (2015) found that in the USA, WTP per month is high (confirmed by Soon and Ahmad, 2015) while WTP per kWh is low (confirmed by Bigerna and Polinori, 2015). This phenomenon arises because the consumption of the average household on electricity is high. For this reason, the formulation of the WTP unit is key to capturing meta-regression results.

Despite differences in sample size, and dependent variable, the results of our meta-regression have been more or less confirmed by other researchers. Studies accounting for a country's share in RE or its share in hydropower confirmed that WTP increases with the share in RE (Chaikumbung,

2021; Ma et al., 2015) and decreases with the share in hydro power (Chaikumbung, 2021). Grilli (2017) added that a country's nuclear share in electricity generation is similarly associated with a reduced WTP. However, the authors did not confirm the influence of country's RE share.

One stylized fact to emerge from these studies is the following - WTP estimates based on CE methods are systematically higher than those elicited using CV methods (Chaikumbung, 2021; Sundt and Rehdanz, 2015). Soon and Ahmad (2015) differentiated in greater depth between the WTP elicitation methods applied in their meta-regression. Their results suggest that not only do differences between CE and CV exist. Differences in WTP arise, even for CV methods. Specifically, differences arise where CV is defined using single- or double-bounded dichotomous choices. Methods applying these dichotomous definitions, systematically lead to lower WTP values for CVs, compared to values obtained using the CE method. In contrast to Soon and Ahmad (2015), Bigerna and Polinori (2015) did not confirm this relationship, but found a negative impact on WTP estimates if payment cards (another CV elicitation method) were used.

Consistent with the findings of Sundt and Rehdanz (2015), other studies similarly confirm that WTP estimates are highly sensitive to the inclusion of certain covariates. This holds true for household characteristics (Grilli, 2017; Ma et al., 2015), income (Chaikumbung, 2021; Grilli, 2017; Ma et al., 2015) and education (Chaikumbung, 2021; Grilli, 2017; Ma et al., 2015). Conversely, the results for consumers' knowledge about RE results, is less clear-cut. Here, the findings are ambiguous. While Sundt and Rehdanz (2015) and Bigerna and Polinori (2015) find a positive effect on WTP values, Grilli (2017) reveals a negative effect. Indeed, in the meta-regression by Ma et al. (2015), this effect is not significant at all.

In contrast to Sundt and Rehdanz (2015), other meta-regressions considered to what extent the source of RE influences WTP estimates. Most of these studies state that the WTP increases for wind and solar power (Chaikumbung, 2021; Grilli, 2017; Ma et al., 2015). In a finding that conflicts with the latter studies, Bigerna and Polinori (2015) reveal the opposite. Turning to biomass, there is similarly a lack of consensus. Specifically, in Ma et al. (2015) there is an inverse relationship between biomass and WTP. A further study by Chaikumbung (2021) reveals a positive association between the two variables. However, hydropower is always associated with an inverse relationship between the response variable and the consumers' WTP (Chaikumbung, 2021; Ma et al., 2015).

Moreover, each of the later meta-regressions add further valuable insights to the literature. Ma et al. (2015) shed light on how survey design influences WTP estimations; i.e., mail surveys and phone interviews increase WTP values. Furthermore, they find that energy consumption decreases WTP per kWh. This finding echoes the evidence by Grilli (2017). Focusing on country-specific variables, such as country's current CO<sub>2</sub>-emissions per capita, Grilli's (2017) results point to increases in the consumers' WTP. Furthermore, he finds that WTP values are higher in local case studies.

Soon and Ahmad (2015) highlight the possibility of a publication bias. However, they were unable to confirm if indeed such a bias existed. More recently, Chaikumbung (2021) confirms this result. Additionally, she reveals that consumers in democratic and liberal countries exhibit a higher WTP for RE. Interestingly, a further result from the latter study directly contradicts findings from the earlier analysis by Grilli (2017) – that CO<sub>2</sub>-emissions per GDP are inversely related to a consumer's WTP. However, this is not necessarily a contradiction where the latter is measured as *CO<sub>2</sub>-emissions per capita*. This disparity between studies underlines the sensitivity of results to variable measurement differences.

Nevertheless, the most recent evidence by Chaikumbung (2021) reveals a positive WTP for RE. Increasing the share of RE in the electricity mix, however, destabilizes the entire electricity grid. Consider the example of Germany – a country which was relatively successful in boosting the share of RE. This expansion, triggered more than a doubling of RE in gross electricity consumption in the decade 2010 to 2020 – from 17 percent to 45.5 percent. Specifically, wind and solar power comprised more than 72 percent of overall production (Umweltbundesamt, 2021). However, wind and solar power are highly weather-dependent. Accordingly, the supply of electricity from these sources fluctuates. This lack of predictability, exacerbates the challenge of balancing demand and supply of electricity in the grid. Unsurprising therefore that RE is associated with an increased risk for electricity outages.

To avoid outages, electricity grids can be balanced by managing either electricity demand or supply. In the absence of efficient energy storage technologies, care is taken to manage the supply side. Such management entails the costly and CO<sub>2</sub> intensive redispatch of electricity from predominantly fossil fuel fired power plants (Vahlenkamp et al., 2016). In this way, electricity planners can deal with peak demand and insufficient electricity supply from renewable energies. On the other hand, demand side management (DSM) aims at matching demand to supply through

the use of price signals (Gellings, 1985). Examples of these signals include electricity tariffs, combined with electricity prices that reflect excess demand and supply from simple time-of-use (TOU) tariffs to complex real-time pricing. Faruqui and Sergici (2010) revealed that these tariffs are effective in reducing peak demand, to a significant extent. The result is a decrease in the need for costly and CO<sub>2</sub> intensive redispatch (Vahlenkamp et al., 2016).

As stated above, almost half of Germany's gross electricity consumption is sourced from RE (Umweltbundesamt, 2021). Currently, Germany relies predominantly on redispatch to balance electricity demand and supply (Vahlenkamp et al., 2016). Alternatively, DSM for private households is limited to traditional TOU tariffs, i.e., day/night-time tariffs (ACER and CEER, 2020). Households with electric heating equipment are applicable for these tariffs. However, these tariffs, are inappropriate for DSM, where planners envisage an expanded role of RE. Accordingly, there is a significant potential for peak-time shifting through the application of more cutting-edge DSM methods, in Germany (Sundt et al., 2020). DSM, however, relies on the active participation of consumers. It follows that the analysis of preferences for various DSM measures in Germany, is of special interest. Armed with such information about consumer preferences, electricity planners are better positioned to implement this policy of applying more sophisticated DSM practices.

Although countries are moving rapidly towards the real-time-pricing of electricity (which would represent the most effective DSM, Nicolson et al., 2018), this dissertation restricts itself to an elicitation of, and discussion of, the preferences for TOU tariffs. Specifically, where these tariffs exceed raised electricity prices – a regime consistent with peak demand. Alternatively, we focus on a second price regime – where the supply of RE is high, and prices accordingly low. This restriction of our analysis to TOU tariffs is necessitated by limited experience of our respondents with these tariffs. In 2021, only two electricity providers in Germany offer tariffs, which reflect day-ahead prices (Bundesnetzagentur and Bundeskartellamt, 2021). For this reason, it is problematic to evaluate dynamic electricity tariffs. Unsurprisingly, and consistent with the low prevalence of real-time-pricing, in 2019, a mere 1,000 from about 40 million private households had access to smart meters, i.e., a digital meter plus a communication device, installed that facilitate these tariffs (ib.).

Comparing TOU and fixed-rate tariffs, researchers agree that the TOU version are less utility maximizing for consumers (see Nicolson et al., 2018 for a meta-analysis). For this reason, consumers must be compensated to accept and choose these tariffs. However, if a country wants to



implement DSM successfully, TOU tariffs need to be widespread. This makes it interesting to dig more deeply into consumers' preferences for TOU tariffs.

In countries where conventional TOU tariffs are less prevalent, studies apply stated preference methods to analyze consumer preferences for these tariffs. Stated preference methods enable researchers to evaluate preferences for non-market goods – such as electricity tariffs that are not yet available to consumers. CEs represent a common method of eliciting preferences for TOU (and more dynamic) tariffs. This method makes use of the random utility model. This model states that consumer's utility is indirectly determined by the attributes of an object rather than directly by the object itself. Accordingly, this method offers researchers a tool for estimating consumers' WTP for certain tariff/contract attributes (McFadden, 1974). As TOU tariffs are expected to decrease consumers' utility – WTP values are negative – preferences are measured as the willingness to accept (WTA). In other words, how much discount on respondents' electricity bill has to be offered to accept the disutility of a TOU tariff.

In general, studies which apply CEs to gauge consumers' WTA for TOU tariffs, tend to highlight a variety of different aspects. Goett et al. (2000) provide an overview of consumers' utility for over 40 electricity contract and tariff attributes. They reveal that utility decreases, as the pricing scheme grows in complexity. This finding has been underpinned by Buryk et al. (2015) who showed that fixed-rate tariffs are favored over TOU tariffs. The latter, in turn, are favored over critical peak pricing. Furthermore, small price differences are preferred to large price differences (Kaufmann et al., 2013). Nevertheless, researchers observe significant preference heterogeneity. This heterogeneity may be alternatively explained by respondents' risk aversion (Schlereth et al., 2018) or information about potential environmental and economic benefits (Buryk et al., 2015). Lastly, it can be explained by expectations over individual financial benefits (Schlereth et al., 2018).

These findings suggest that in the context of billing for electricity, consumers' dislike unpredictability. Indirectly, the findings signal that consumers are aware that they need to adapt their behavior to avoid electricity consumption when electricity prices are high. This results in the idea that automated external control of appliances with high electricity consumption might be evaluated as benefit by consumers. Consumers would, therefore, avoid electricity consumption when prices are high without effort. To acknowledge this, more recent CEs included opportunities to allow for external control of heating and/or electricity consumption. Contrary to expectations, Broberg and Persson (2016) as well as Richter and Pollitt (2018) find that external control of

electricity consumption tend to decrease consumers' utility. However, they did not specify which appliances should be controlled. Furthermore, consumers are less sensitive to heating control than to electricity control (Ruokamo et al., 2019). Thus, preferences for external control over appliances might in fact differ by the type of appliance.

Apart from the study by Schlereth et al. (2018), there is no further CE study for Germany, which deals with TOU tariffs in Germany. That is, until the 2020 study by Sundt et al. (2020). We can compare the two studies here. In Schlereth et al. (2018), their CE focused on uncertainty about financial benefits and additional costs, instead of certain tariff/contract attributes. Therefore, knowledge about preferences for TOU tariffs in Germany was limited. As described above, we already know that consumers demand a compensation for choosing these tariffs, while the WTA amount differs among consumers. Accordingly, the second paper of this dissertation (Sundt et al., 2020, Chapter 3) focuses on the external control of appliances. Specifically, it addresses the following research question:

*Are German consumers willing to choose a TOU tariff, what determines their willingness to accept (WTA), and how does external control of certain appliances change their preferences?*

To answer this question, we use results of a 2017 choice experiment on TOU tariffs. The novelty of this CE is that we include an option for external control of specified appliances. Respondents are given to understand that the electricity consumption of appliances can be automatically controlled, during times with high electricity prices. This service is expected to decrease the adaptive effort required of consumers (decreasing WTA). On the other hand, the service also restricts the consumers' freedom of choice (increasing WTA). Our findings are revealing. How these effects are evaluated by consumers, do indeed differ by appliance. For example, we found that respondents perceive higher marginal utility in being able to exercise external control over their washing machine (negative effect on WTA). However, the same intuition does not apply for external control over their freezer, where there is a decrease in marginal utility (positive effect on WTA).

Additionally, we found significant preference heterogeneity that is driven by the decision strategy of respondents. This heterogeneity allows us to group respondents into four mutually exclusive groups. About 70% of respondents are potential TOU tariff adapters, i.e., respondents who always chose a TOU tariff but not always the maximum discount (36%), and respondents who revealed no

dominant strategy (34%). The remaining respondents either always chose a fixed rate tariff (20%) or the tariff offering the maximum discount (9%).

WTA estimates differ significantly across these groups for any tariff attribute. For example, on average, respondents would demand around 14€ per month to accept a TOU tariff with four hours of high electricity prices. However, if you only look at respondents who always chose a fixed rate tariff, this amount increases to 82€. Respondents we identified as potential TOU tariff adapters exhibit significantly lower WTA values; i.e., 25€ (if they revealed no dominant strategy) and 6€ (if they always chose a TOU tariff but not focused on the maximum discount). Thus, potential TOU tariff adapters exhibit a significantly lower WTA than those who always chose a fixed rate tariff.

This preference heterogeneity cannot be explained by common socio-demographic characteristics. This finding echoes those of previous results (e.g., Broberg and Persson 2016). Furthermore, previous studies find inconclusive results for gender effects: While Hall et al. (2016) state that women are less in favor of TOU tariffs (focus group in Australia), Buryk et al. (2015) estimate lower WTA values for women (CE in the USA and the EU). However, identifying the profile of consumers who are willing to choose TOU tariffs is crucial to increase the acceptance of these tariffs

For this reason, some researchers (Buryk et al., 2015; Nicolson et al., 2017; Schlereth et al., 2018; Yang et al., 2018) analyzed if respondents' attitudes might explain this preference heterogeneity. Unlike most socio-demographic characteristics, risk aversion (Nicolson et al., 2017; Schlereth et al., 2018), information on environmental and economic benefits (Buryk et al., 2015), and general knowledge about TOU tariffs (Yang et al., 2018) were all found to significantly influence preferences for TOU tariffs. A shortcoming of these studies is that they solely focus on one aspect at a time (e.g., risk aversion) and do not rely explicitly on behavioral theories. Behavioral theories, however, have a long tradition in explaining respondents' environmentally friendly behavior (Steg and Vlek, 2009).

In energy economics, researchers interpret preferences for, or adaption of measures that aim for a more environmentally friendly "use" of energy (such as RE expansion) as pro-environmental behavior. Pro-environmental behavior, in general, is mainly explained by the Theory of Planned Behavior (TPB) or the Value-Belief norm (VBN) (Steg and Vlek, 2009). The TPB (Ajzen, 1991) implies that an individual's intention to behave relies on her attitude towards this behavior, her

subjective norms, and her perception of behavior control. In contrast to the TPB, the VBN (Stern, 2000) explains behavior based on an individual's moral and norms. These norms include an individual's values, her awareness of consequences and needs, and her responsibility to action.

In the broader context of electricity tariff choice, studies have already shown the significance of elements of TPB and VBN in explaining preference heterogeneity. Wang et al. (2012) reveal that preferences for electricity tariffs with prices tied to electricity consumption are driven by environmental/global warming awareness, energy saving behavior, social pressure, and electricity literacy. Preferences for external control of electricity consumption depend on descriptive norms (Gołębiowska et al., 2020). Furthermore, acceptance of load-restrictions increases if respondents are previously informed about the positive impact of this measure on transitioning to RE (Broberg et al., 2021).

These previous findings suggest that TPB and VBN might help to explain a significant part of the heterogeneity in preference that we observed in the context of TOU tariffs. Accordingly, the third Paper of this dissertation (Sundt, 2021, Chapter 4), discusses the following research question:

*Do elements of TPB and VBN, measured by common factors, explain a significant share in consumers' stated willingness to choose TOU tariffs in Germany?*

To answer this question, I use online, German survey data, which I collected in 2016. To begin with, I perform an exploratory factor analysis on 25 attitudinal statements concerning motivation and social norms, the perceived impacts of TOU tariffs, climate change, and general electricity saving measures. This factor analysis allows me to discriminate four individual factors. These factors measure as follows – (1) Positive Attitude towards TOU Tariffs, (2) Negative Attitude towards TOU Tariffs, (3) Climate Change Awareness, and (4) Belief in Energy Saving Measures. In a second step, I estimate the stated willingness of respondents to purchase a TOU tariff. Importantly, these factors (and additional covariates) are included in the regressions as explanatory variables. Positive and negative attitudes are highly significant in helping to explain the preference for TOU tariffs. Alternatively, awareness of climate change and belief in energy saving measures exercises less influence. Furthermore, willingness to take risk and prior experience with TOU tariffs, constitute important additional factors. Interestingly, gender only has an indirect effect on preferences, since women tend to have a more positive attitude towards TOU tariffs.

In conclusion, results of this dissertation suggest that consumers exhibit a remarkable acceptance for electricity generated by RE (Sundt and Rehdanz, 2015). Nevertheless, integrating RE into the electricity grid is not without its problems. Even though DSM constitutes a cheap and feasible method to manage these issues, German consumers on average exhibit a dislike for TOU tariffs. However, we observe significant preference heterogeneity and are able to identify a significant share in respondents who would choose TOU tariffs over fixed-rate tariffs (Sundt et al., 2020). Attitudes towards TOU tariffs significantly influence this preference heterogeneity (Sundt, 2021). Policy makers should, therefore, increase consumers' knowledge about the environmental and economic benefits of TOU tariffs. In parallel, policy makers should encourage utility companies to offer tariffs that enable DSM. However, consumers would additionally require smart meters – which are able to measure households' electricity consumption every 15-minutes. Smart meters are necessary to lock in to the dynamics of price changes that occur in modern TOU tariffs. Currently, smart meters are not mandatory for common private consumers in Germany. The installation of such devices would go some way towards facilitating the expansion of energy from renewable sources.

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## 2 First Paper: Consumers' willingness to pay for green electricity: A meta-analysis of the literature

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**Abstract:** At present, electricity generated from power plants using renewable sources costs more than electricity generated from power plants using conventional fuels. Consumers bear these expenses directly or indirectly through higher prices for renewable energy or taxes. The number of studies published over the last few years focusing on people's preferences for renewables has increased steadily, making it more and more difficult to identify key explanatory factors that determine people's willingness-to-pay (WTP) for renewables. We present results of a meta-regression on valuation of consumer preferences for a larger share of renewable energy in their electricity mix. Our meta-regression results reveal a number of important factors that explain the differences in WTP values for renewable energy. Different valuation methods show widely different values, with choice experiments producing the highest estimates. Our results further indicate that consumers' WTP for green electricity differs by source, with hydropower being the least valued. Variables that are often omitted from primary valuation studies are important in explaining differences in values. These variables describe individual and household characteristics as well as information on the type of power plant that will be replaced by renewables. Further, the marginal effect of a survey conducted in the US is pronounced. We also assess the potential for using the results for out-of-sample value transfer and find a median error of 21%.

**Keywords:** Meta-analysis; Renewable energy; Valuation; Value transfer; Willingness to pay

## 2.1 Introduction

Many industrialized countries have ambitious renewable energy targets to mitigate climate change and/or to gain independence of fossil fuel imports. At present, electricity generated from power plants using renewables is more costly compared with those using conventional fuels. The difference is paid for by the consumers either directly through a higher price for renewable energy or indirectly through taxes. As a response to this, a number of studies have investigated consumer preference and willingness to pay (WTP) for larger shares of green electricity (most recently, Kim et al., 2013). The number of such studies published over the last few years focusing on people's preferences for renewables has increased steadily, thus resulting in a flood of data, which has made it increasingly more difficult to identify key explanatory factors that determine people's WTP for renewables. Studies vary widely in the energy-related characteristics they analyze (such as energy mix, siting of new power plants, infrastructure investments, etc.), the geographical location and the valuation technique employed.

Meta-analysis is a quantitative analysis of summary indicators reported in a series of similar empirical studies (Stanley, 2001). A quantitative meta-analysis ensures global comparability of WTP for renewable energy and provides evidence for common preferences. In our meta-analysis, we investigate the mean WTP per household per month and per kilowatt-hour to determine global preferences for renewable energy. Based on a meta-regression, we analyze whether differences in WTP exist by country, whether results on explanatory variables for WTP differ and the extent to which survey design influences WTP estimates. Because costs associated with performing a study that assesses WTP for green electricity are considerable, we explore the use of “value transfer” to non-valued sites/countries as an alternative to primary valuation.

Previous meta-analyses on preferences for renewable energy focus primarily on public acceptance of wind power (e.g., Aitken, 2010) and on the corresponding “not in my backyard” (NIMBY) phenomenon (van der Horst, 2007). While meta-analysis in combination with meta-regression is often used in ecosystem valuations (e.g., coral reefs: Brander et al., 2007), to our knowledge, there does not exist a meta-regression analysis on WTP for renewable energy.

The structure of our paper is as follows. Section 2.2 reviews the literature regarding consumer WTP for renewable energy in the electricity mix and outlines the type of studies used in our analysis - those focusing on green electricity. Section 2.3 presents our data and describes results of individual studies as well as summary statistics of WTP estimates. Section 2.4 presents the specification of

the meta-regression, and the methods used to judge quality of the value transfer. Section 2.5 discusses the results of the meta-regression, and explores the validity, efficiency and robustness of our results when transferring values. Section 2.6 concludes the paper.

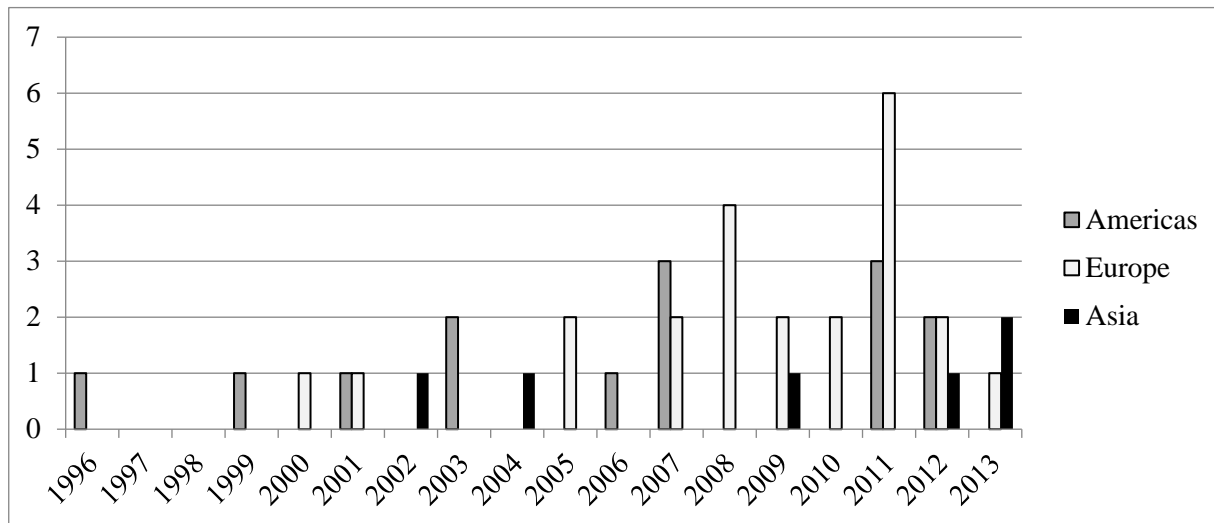
## **2.2 Overview of the willingness-to-pay for renewable energy literature**

An extensive search for published and unpublished (working papers and reports) studies relating to WTP for renewable energy was conducted on Web of Science, EconBiz, and Google Scholar and following references of relevant studies. The search spanned from end-December 2013 to end-January 2014 using the phrase “willingness to pay” in combination with each of the following renewable energy related words: (1) renewable, (2) green, (3) energy, (4) electricity, (5) power, (6) biomass, (7) wind, (8) solar, and (9) photovoltaic, (10) hydro; this implies that search output is likely to omit non-English related studies. Using this search algorithm, we collected 101 studies based on stated preference surveys that estimated respondents' WTP for renewable energy. Out of the 101 studies 43 studies provides estimates of WTP for a higher share of renewable energy in the electricity mix. These studies are more readily comparable in a meta-analysis than a larger set of studies characterized by other key aspects, including studies that, for example, focus on the siting of wind farms.

The earliest study we found in the category 'electricity mix' was published by Farhar and Houston (1996). They measured the WTP for electricity from renewables in the United States (US). Between 1996 and 2006, only one or two studies per year were published. After 2006, the number of publications increased, with an average of 4.4 studies per year being published between 2007 and 2013, most of them with a focus on European countries or regions.

Figure 2.1 shows that over space and time, studies are very unevenly distributed. Overall, we count 23 studies for Europe, twelve for the Americas and six for Asia. At the country level, most of the surveys were conducted in the US (twelve publications), followed by Germany (seven publications) and the United Kingdom (UK, four publications). While studies using data for the US or the UK are relatively evenly distributed over time, the first studies using German survey data were published in 2005 (Gossling et al., 2005; Menges et al., 2005).

**Figure 2.1: Number of Published Studies by Year and Continent**



Note: Sample size = 23.

Over time, researchers considered that more factors were involved in determining people's WTP, and the information they used provided increasingly more insight. For instance, several authors reviewed the influence of payment arrangements on the WTP for renewable energy, e.g., Menges and Traub (2008), Soliño et al. (2009) and Soliño et al. (2012). Other authors compared the current electricity mixes with stated consumer preferences, e.g., Grösche and Schröder (2011) and Kaenzig et al. (2013).

### 2.3 Description of data

Among the 43 studies, we exclude 25 from the meta-regression because of sample selection bias (e.g., Gossling et al., 2005) or unsuitable units of WTP estimates; that is, inconvertible. For instance, some authors express WTP as a percentage of the current electricity bill (e.g., Liu et al., 2013) or as the probability to be willing to pay anything at all (e.g., Batley et al., 2001). Further, we exclude one survey conducted in India (Chakrabarti and Chakrabarti, 2002). This study focused on rural electrification and, to a much lesser extent, on India's electricity mix.

Our final meta-regression consists of 85 WTP values that are ascertained from 18 studies (see Table 2.1). This corresponds to an average of 4.72 WTP values per study. We abstract the largest data sample (19 observations) from the study by Borchers et al. (2007), a choice experiment eliciting preferences for electricity for different renewable energy sources that was conducted in Newcastle

County, Delaware, USA. As the number of observations (WTP estimates) per study varies, we use sampling weights to give studies contributing fewer observations, correspondingly, greater weight.

**Table 2.1: Studies Included in the Meta-Regression**

Author (year)	Year of Survey	Country	Coverage	Method	# WTP values
Aldy et al. (2012)	2011	US	national	CV	3
Aravena et al. (2012)	2008	Chile	local	CV	4
Bigerna and Polinori (2011)	2007	Italy	national	CV	9
Bollino (2009)	2006	Italy	national	CV	9
Borchers et al. (2007)	2006	US	local	CE	19
Cicia et al. (2012)	2009	Italy	national	CE	3
Gracia et al. (2012)	2009	Spain	local	CE	3
Hanemann et al. (2011)	2009	Spain	national	CV	1
Kaenzig et al. (2013)	2009	Germany	national	CE	3
Kim et al. (2013)	2008	South Korea	national	CV	4
Komarek et al. (2011)	2009	US	local	CE	9
Kosenius and Ollikainen (2012)	2008	Finland	national	CE	6
Nomura and Akai (2004)	2000	Japan	national	CV	3
Soliño et al. (2009)	2006	Spain	regional	CV	4
Susaeta et al. (2011)	2008	US	regional	CE	1
Yoo and Kwak (2009)	2008	South Korea	local	CV	2
Zhang and Wu (2012)	2010	China	regional	CV	1
Zografakis et al. (2010)	2007	Greece	regional	CV	1

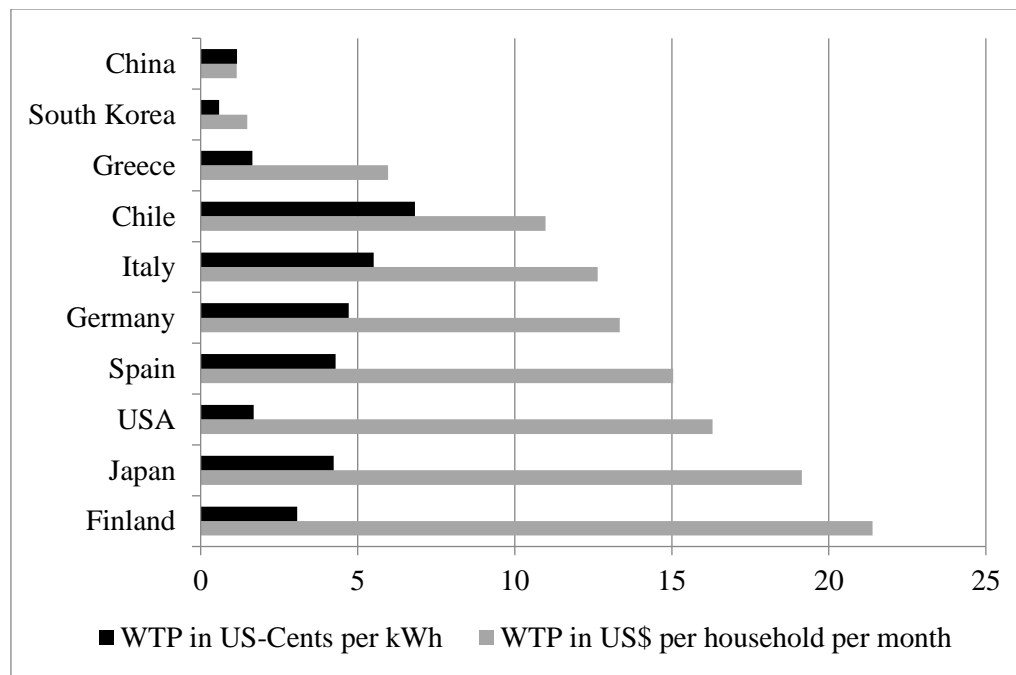
*Note: CV: Contingent Valuation Method; CE: Choice Experiment / Conjoint Analysis.*

The 18 studies were published in 2004, 2007 or between 2009 and 2013. The corresponding surveys were conducted in nine developed countries and one developing country (China) on three continents (Europe, the Americas and Asia) either in 2000 or between 2006 and 2011. Multiple surveys were conducted in the US (3), Spain (3), Italy (3) and South Korea (2). One-half of the surveys were national, one-quarter were local and another quarter were regional. Each study in our sample used either contingent valuation techniques (twelve studies) or choice modelling approaches (six studies) to determine WTP. Two of the 18 studies are working papers (Bigerna and Polinori, 2011; Kosenius and Ollikainen, 2012). Of our 85 WTP values, 41 are gained by contingent valuation analyses and 44 by choice modelling.

Our dependent variable is the WTP for an increase in renewable energy in the current electricity mix. While results of contingent valuation studies are most often expressed as mean WTP, results of choice experiments are expressed as marginal WTP. If the “status quo” option belongs to the selectable alternatives of the choice experiment and the marginal WTP is based on the “status quo”,

we treat the marginal WTP as the mean WTP. Further, we use only WTP values in the meta-regression that can be interpreted as “WTP for a higher renewable energy share in the current electricity mix” and measure in fixed units of currency per time frame and household. Next, we approximate the WTP per kilowatt-hour to adjust the WTP to average electricity usage per capita.<sup>2</sup> A remarkable fact is the relatively high electricity consumption per capita in Finland and the US, which is at least twice as high as the electricity consumption of Japan, the third highest in the sample.

**Figure 2.2: Mean WTP by Country**



To ensure comparability, we convert WTP values in US\$ per household per month and adjust them to 2010 prices using purchasing power parity exchange rates.<sup>3</sup> In our sample, the mean WTP for a higher renewable energy share in the electricity mix is US\$ 13.13 per household per month and the median WTP is US\$ 11.67. The lowest WTP (US\$ 1.00) is found by Borchers et al. (2007) for an increase in biomass in the US. Hanemann et al. (2011) report the highest WTP (US\$ 43.01) for an increase in renewables in Spain. Overall, the distribution of WTP values is positive skewed. When

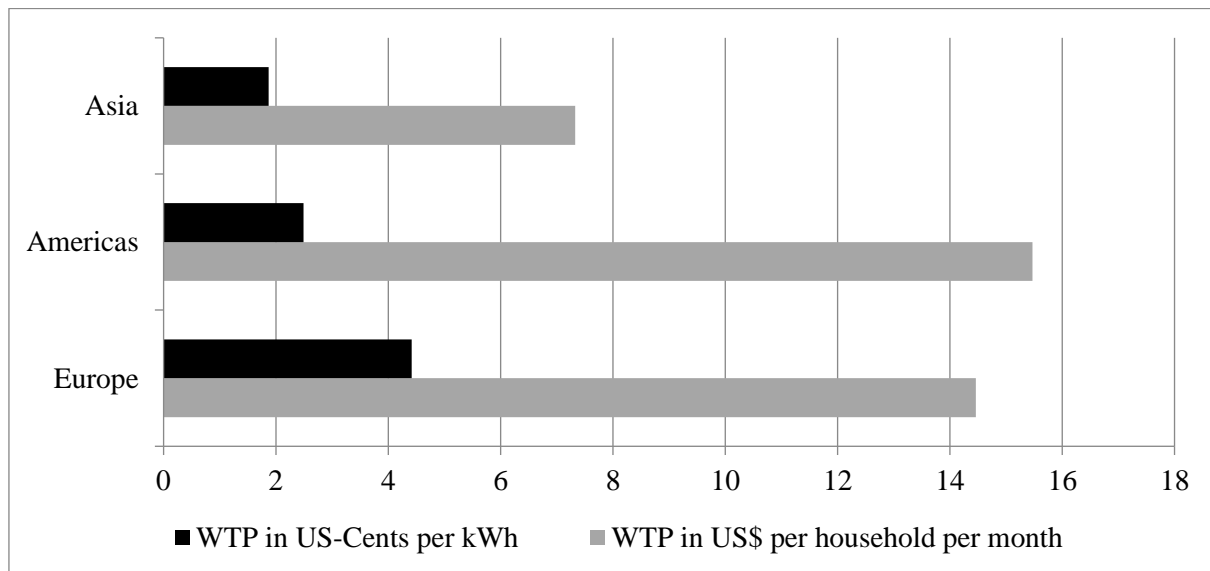
<sup>2</sup> For this, we used information on total residential energy consumption and total population (OECD/IEA (2014a, 2014b), as well as information on average household size (Eurostat 2013; National Bureau of Statistics of China 2010; OECD 2012; Statistics Japan 2013; U.S. Census Bureau 2013).

<sup>3</sup> Data retrieved from OECD (n.d.).

WTP is measured in kilowatt-hours, the mean WTP is US-Cents 3.18/ kilowatt-hour and the median WTP is US-Cents 1.95/ kilowatt-hour.

At the country level (see Figure 2.2), the highest mean WTP per household (US\$ 21.39), which corresponds to a mean WTP per kilowatt-hour of US-Cents 3.07, is observed for Finland. However, we observe the opposite for Chile, the country with the second lowest residential energy consumption per capita. Here, the WTP per household (US\$ 10.98) is below average while the WTP per kilowatt-hour (US-Cents 6.82) is ranked highest. Furthermore, China and South Korea have the lowest WTP per household and per kilowatt-hour.

**Figure 2.3: Mean WTP by Continent**



Although Japan demonstrates an above average WTP per household, the average WTP for Asia (see Figure 2.3) is half that of European countries and countries in the Americas, which are quite similar. With respect to the average WTP per kilowatt-hour, the WTP for Asia is the lowest. However, in contrast to the WTP per household, there exists a significant difference between the mean WTP for the Americas (US-Cents 2.49) and for Europe (US-Cents 4.43).

Several hypotheses exist regarding the factors that explain the differences in the studies' WTP values. In our sample, most studies include income as an explanatory variable. Of the 18 studies only one presents a slightly negative influence of income on WTP (Susaeta et al., 2011), but the estimated coefficient is statistically insignificant. All others find a positive effect of income on WTP.



Frequently, age and price variables are considered as well. In general, older people seem to have a lower WTP, but Aldy et al. (2012) find the opposite. Borchers et al. (2007) distinguish different age groups and find people over 50 years of age and below 30 years of age reported a lower WTP. This finding could be correlated with the positive effect of income, which is lower for these groups. All studies report negative coefficients for electricity prices. *Ceteris paribus*, higher electricity prices reduce respondent's WTP for a specific tariff. Half of the studies explain differences in studies' WTP values by gender, education or environmental attitudes, such as a belief in climate change. With respect to gender, in all studies, WTP is lower for male than for female respondents. Education has a positive effect on WTP. An exception, however, is Yoo and Kwak (2009). Not surprisingly, environmental concerns increase peoples' WTPs. Borchers et al. (2007) find a negative effect on WTP when respondents are more concerned about the environmental impacts of electricity generation.

Some authors include alternative renewable energy sources, knowledge about renewable energy or regional aspects. Overall, renewable energy sources increase WTP for electricity. Borchers et al. (2007) and Gracia et al. (2012) find evidence that electricity generated from solar is preferred over other alternatives. While US-Americans exhibit a positive WTP for nuclear power (Borchers et al., 2007), Germans prefer the electricity mix with a 25% share in natural gas over the mix with a 25% share in nuclear power (Kaenzig et al., 2013).

Studies that consider knowledge about renewable energy show varying results, which can be explained by the various ways in which knowledge is controlled. For example, Bollino (2009) uses factual questions about renewable energy, and participants who answer these questions correctly tend to exhibit lower WTP values. Kim et al. (2013) obtain similar results when eliciting peoples' knowledge of the ratio of renewables in total energy generation. However, participants who demonstrate awareness of the fact that electricity can be generated from photovoltaic and biomass report higher WTPs (Zografakis et al., 2010).

While six studies compare WTP by region, the results are survey specific. For example, Kosenius and Ollikainen (2012) distinguish WTP for woody biomass by East Finnish and all other Finnish people. In East Finland, the WTP for forest biomass is higher than it is in the rest of Finland. The authors contend that this is due to the high forest coverage of East Finland. Kim et al. (2013) state a lower WTP for people living in rural areas of Korea. Susaeta et al. (2011) find no differences in WTP when comparing the US-states Arkansas, Florida and Virginia.

Furthermore, in our sample, only four studies take household characteristics into account, including, e.g., Aldy et al. (2012) and Bigerna and Polinori (2011), who find a decreasing WTP for larger households.

## 2.4 Meta-analysis and value transfer

### 2.4.1 Meta-regression model

In our meta-regression, we investigate the marginal effects of different study designs on the WTP for a higher renewable energy share in the electricity mix. In our model, the dependent variable is a vector  $y$ , which contains either WTP values measured in US\$ per month per household in 2010 prices or WTP values measured in US-Cents per kilowatt-hour. The independent variables (Table 2.2) belong to two matrices. Matrix  $X_C$  includes country-specific characteristics; matrix  $X_S$  includes Survey-specific characteristics. Country-specific characteristics contain information on a country's renewable energy share in total energy production for a given survey year differentiated by hydropower and other renewable energy sources (OECD/IEA, 2014b). Survey-specific characteristics are captured by a set of dummy variables controlling for the valuation method, the design of the WTP scenario, and the type of explanatory variables considered in the original WTP estimation. Note that the latter set of variables is not respondent-specific, they signal if a study considers certain respondent-specific information as explanatory variables in the regression. Some of the studies control, for example, for household income or education level as a determinant of a person's WTP while other studies omit these variables from their regression analysis.

**Table 2.2: Explanatory Variables in Meta-Regression**

Variable	Definition
<b>Country-specific variables:</b>	
RE_SHARE	Percentage share renewables of total energy production (without hydro)
HYDRO_SHARE	Percentage share in hydro power of total energy production
LN_RE	Ln of percentage share renewables of total energy production (without hydro)
LN_HYDRO	Ln of percentage share in hydro power of total energy production
<b>Survey-specific variables:</b>	
YEAR	Year of survey, base 2000
USA	Dummy: 1 = USA; 0 = Other country
METHOD_CV	Dummy: 1 = Contingent valuation; 0 = Choice experiment
UN_SPEC	Dummy: 1 = No specification which kind of power plant should be substituted; 0 = Specified
ATT_KNOW	Dummy: 1 = Knowledge about RE included in WTP estimation; 0 = Not included
ATT_HH	Dummy: 1 = Household variable included in WTP estimation; 0 = Not included
ATT_INC	Dummy: 1 = Income variable included in WTP estimation; 0 = Not included
ATT_EDU	Dummy: 1 = Education included in WTP estimation; 0 = Not included

It is plausible to assume that the survey design has a significant influence on the estimated WTP. In our case, either contingent valuation or choice modelling is used to elicit WTP. Previous environmental valuation studies that compared results from contingent valuation and choice experiments lead to inconclusive results. In some studies, WTP estimates of choice experiments are larger compared to WTP estimates of contingent valuation (e.g., Hanley et al., 1998), some studies find the opposite (e.g., Boxall et al., 1996). For this reason, the dummy variable *METHOD\_CV* controls for methodology. Further, as we expect the WTP scenario to influence WTP estimates, we add the dummy variable *UN\_SPEC* to identify those observations where information on the substitute for the renewable is missing.

Further, we suspect an influence by the kind of variables which are chosen as explanatory variables to estimate WTP; e.g., *ATT\_EDU* identifies those observations where information of a respondent's education level was controlled for.

We improve the quality of the estimation results by taking the natural logarithm of the dependent variable. This leads to the following semi-log linear regression model:

$$\ln(y_i) = \alpha + \beta_C X_{Ci} + \beta_S X_{Si} + \varepsilon_i \quad (2.1)$$

where  $\alpha$  is a constant term,  $\beta_C$  and  $\beta_S$  are vectors of coefficients that contain information about the marginal effects,  $\varepsilon_i$  is the error term corresponding to WTP value  $y_i$  with  $i = 1, \dots, n$  and  $n$  is the number of extracted WTP values.

In meta-regression either weighted regression models, panel models, or multilevel models are commonly used to account for individual study effects (Nelson and Kennedy, 2009). In a weighted regression, each study has the same weight independent of the number of WTP values gained from the individual study. Panel models distinguish between fixed and random effects. In a fixed effects model it is assumed that each study has a fixed individual effect. Estimating a fixed effects model leads to the within estimator, which explains the effects within a study. In a random effects model it is assumed that each study has a random individual effect. Estimating a random effects model commonly leads to the general least squares estimator, which explains the effects between and within studies. A multilevel model is a mixture of a random and a fixed effects model, that is, it allows for random and fixed effects.

Panel models or multilevel models are, unfortunately, not appropriate given our data set. The variables we use to explain differences in estimated WTP rarely vary within the studies we include. Therefore, these variables would be dropped due to collinearity when estimating panel models. Nevertheless, we expect that WTP estimates provided by the same study are somehow correlated and we use a weighted linear regression to control for it. As the number of observations (WTP estimates) per study varies, sampling weights were used to give studies contributing fewer observations, correspondingly, greater weight. The statistic package STATA automatically estimates the variance covariance using the Huber-White estimator, and therefore produces robust standard errors.<sup>4</sup>

#### **2.4.2 Quality of value transfer**

Environmental value transfer (see Brouwer, 2000) is often used to adapt results from previous surveys from a study site to a policy site. A main advantage of environmental value transfer is its low cost compared with a primary valuation study at the policy site.

Three general approaches exist to transfer values - direct value transfer, benefit function transfer and meta-analysis. Using direct value transfer, the study site and the policy site should be similar in their characteristics (otherwise adjustments are necessary) as estimated value(s) of one or more primary studies are simply transferred to the policy site. With respect to function value transfer, the second approach, values are transferred to a policy site based on the site's own characteristics using the value transfer function of the study site. Here, we follow the third approach by using results of a meta-analysis to transfer values. Comparing the three approaches, value transfer based on meta-analysis has the advantage of using information from a number of studies. Also, it tends to perform better (Engel, 2002; Rosenberger and Phipps, 2002).

Despite value transfer based on meta-analysis being the preferred approach, this type of value transfer might produce substantial transfer errors as well. This is particularly the case when the data underlying the estimated relationship in the meta-regression does not represent well the site to which values are being transferred to. Other types of errors occur, because dummy variables do not capture the true variation in the characteristics they are supposed to measure. Further, it is often difficult to capture important quality and/or quantity differences across studies (e.g., as they relate

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<sup>4</sup> This procedure takes into account issues concerning heterogeneity and lack of normality.

to the description of the primary WTP scenario). Finally, primary valuation studies are also a source of errors.

We test the out-of-sample forecast performance of our models similar to Brander et al. (2006). We use an  $n - 1$  data splitting technique to estimate  $n$  meta-regression value transfer functions. Each value transfer function is based on  $n - 1$  observations, to predict the WTP<sup>5</sup>,  $\hat{y}_i$  for the omitted study. As suggested and explained by Shrestha and Loomis (2003, 2001), we explore the validity of this predicted WTP in four different ways; we use two Student's t-tests, which test (1) for equal means and (2) for correlation, and (3) we investigate the absolute (percentage) error, and (4) we regress observed WTP on predicted WTP.

First, we perform a paired Student's t-test which inspects whether the mean of the predicted values is significantly different from the mean of the observed values. This leads to the following null hypothesis:  $H_0: 1/n \sum_{i=1}^n (y_i - \hat{y}_i) = 0$ ; that is, on average there is no difference between predicted values and the observed value from a specific study. The hypothesis can be rejected if the p-value is smaller than a previously defined significance level. If we reject the null hypothesis there is evidence that our meta-regression is incorrect.

Second, we perform another Student's t-test to analyze the significance of Pearson's correlation coefficient. Pearson's correlation coefficient  $r \in [-1,1]$  measures the linear correlation of two metric asymptotically normal distributed variables, whereupon, a large positive value corresponds to a strong linear correlation between predicted and observed WTP value. The null hypothesis of the Student's t-test is:  $H_0: r(y, \hat{y}) = 0$ . Thus, if the p-value is significant the null hypothesis has to be rejected, and there is, indeed, a significant correlation between both values.

Third, we evaluate the quality of the value transfer by calculating the absolute (percentage) error and the mean absolute percentage error; defined as:  $MAPE = 1/n \sum_{i=1}^n |(y_i - \hat{y}_i)/y_i|$ . *MAPE* is commonly used to judge on the quality of the average forecasting performance of meta-regression value transfer functions (e.g., Brander et al., 2006).

Forth, we investigate the linear relationship of the observed WTP and the predicted WTP by performing an ordinary least squares regression by using the following model:

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<sup>5</sup> Because of the semi-log-linear model we need to adjust the predicted WTP ( $\hat{y}$ ) for the estimated variance  $\widehat{\sigma}^2$ , which is the squared Root-MSE:  $\hat{y} = \exp\{x\hat{\beta} + \widehat{\sigma}^2/2\}$  (Greene 2012).

$$\ln(y_i) = \alpha + \beta \widehat{\ln(y_i)} + \varepsilon_i \quad (2.2)$$

In case of a perfectly forecasting meta-regression transfer function (equation 1), the parameters should have the following sizes:  $\alpha = 0$  and  $\beta = 1$ . We test the null hypothesis  $\alpha = 0$  with a standard t-test, and the null hypothesis  $\beta = 1$  with an F-test. If the null hypothesis is rejected, that is the p-value is smaller than a previously defined significance level, the value transfer is biased.

## 2.5 Results

### 2.5.1 Meta-regression

Table 2.3 presents the meta-regression results for the two dependent variables (*LN\_WTP* and *LN\_WTP\_KWH*) and two models. The two models differ with respect to the specification of on a country's renewable energy share in total energy production. Model 1 uses the percentage shares (*RE\_SHARE* and *HYDRO\_SHARE*), and Model 2 uses the natural logarithm of the shares (*LN\_RE* and *LN\_HYDRO*).<sup>6</sup> Additionally, we estimated each model with and without interaction terms of *ATT\_EDU* and *ATT\_KNOW*. Both variables are highly correlated but omitting one of them seems misleading since we have studies in our sample that include only one of the two variables in their specifications.

Model 1 with interaction effects is our preferred model for estimating WTP per household per month (*LN\_WTP*). Model 1 outperforms Model 2 regarding every quality measure (Adjusted R-squares, Bayesian and Akaike's Information Criteria). Further, Model 2 fails the Ramsey RESET test for functional form (Ramsey, 1969).<sup>7</sup> The corresponding p-value, which is close to zero, points to a misspecification of Model 2. Therefore, Model 2 is not further considered.<sup>8</sup>

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<sup>6</sup> We also tried a model including the squared renewable energy shares, but the model performed worse than those included in Table 3. Furthermore, the coefficients for the squared shares were not significant.

<sup>7</sup> More specifically, the RESET test tests whether non-linear combinations of the fitted values have any power in explaining the dependent variable. A significant p-value of the F-test supports the hypothesis of a misspecified model.

<sup>8</sup> Estimating the models without weights has a negligible effect on the size of the estimated coefficients and the significance of variables, but reduces the explanatory power of the models significantly.

**Table 2.3: Results of Meta-Regression by Model**

Variable	LN_WTP				LN_WTP_KWH			
	Model 1		Model 2		Model 1		Model 2	
	No Interaction	Interaction	No Interaction	Interaction	No Interaction	Interaction	No Interaction	Interaction
YEAR	-0.5153***	<b>-0.6067***</b>	-0.3239***	-0.3588***	-0.3841***	-0.4510***	-0.2767***	-0.3045***
RE_SHARE	0.2773***	<b>0.3100***</b>	-	-	0.1904***	0.2144***	-	-
HYDRO_SHARE	-0.0714***	<b>-0.0755***</b>	-	-	-0.0482**	-0.0512***	-	-
LN_RE	-	-	2.4442***	2.5377***	-	-	2.0655***	2.1397***
LN_HYDRO	-	-	-1.9863***	-2.0946***	-	-	-1.6679***	-1.7538***
USA	2.4693***	<b>2.6596***</b>	1.3647***	1.3613***	0.8076**	0.9470***	0.2088	0.2061
METHOD_CV	1.0603***	<b>0.9091**</b>	0.0218	-0.1108	0.9269**	0.8161*	0.2597	0.1545
UN_SPEC	-2.3546***	<b>-2.6130***</b>	-0.5226	-0.5994*	-2.2140***	-2.4033***	-0.8745***	-0.9355***
ATT_HH	-1.2335***	<b>-1.0065***</b>	-0.6202	-0.5185	-1.2557***	-1.0893**	-0.8701***	-0.7895**
ATT_INC	0.7563***	<b>0.8483***</b>	0.3690	0.4511	0.7548***	0.8222***	0.4066	0.4717**
ATT_KNOW	-0.3938	-	-0.4034	-	-0.5223*	-	-0.4004	-
ATT_EDU	2.2437***	-	1.3793***	-	2.0527***	-	1.6304***	-
ATT_KNOW	-	<b>1.4272***</b>	-	0.4667	-	0.8123**	-	0.2899
ATT_EDU	-	<b>2.8408***</b>	-	1.6485***	-	2.4904***	-	1.8440***
Interaction ATT_KNOWxATT_EDU	-	<b>2.0746***</b>	-	0.9881**	-	1.6952***	-	1.2396***
Constant	4.4658***	<b>4.8779***</b>	1.9407***	2.1607***	2.9012***	3.2032***	0.8307	1.0053*
F-Statistic	45.03	-	55.59	-	49.31	-	55.77	-
Adjusted R-squared	0.6955	<b>0.7700</b>	0.5924	0.6088	0.6241	0.6695	0.6399	0.6515
Root-MSE	0.5996	<b>0.5211</b>	0.6937	0.6796	0.6089	0.5710	0.5960	0.5863
RESET [p<F]	0.3242	<b>0.1530</b>	0.0021	0.0000	0.3318	0.9427	0.0553	0.0821
AIC	164.4742	<b>139.4844</b>	189.2672	184.6301	167.1037	155.0083	163.4576	159.5188
BIC	191.3434	<b>166.3536</b>	216.1363	211.4993	193.9729	181.8774	190.2367	186.388

n=85  
Significance: \*: 10%-level; \*\*: 5%-level; \*\*\*: 1%-level

*AIC: Akaike's information criterion; BIC: Bayesian information criterion.*

Using WTP per kilowatt-hour (*LN\_WTP\_KWH*) as dependent variable, again, Model 1 with interaction effects is our preferred model. Model 2 with and without interaction effects fail the RESET test, which points to a misspecification of the models.<sup>9</sup>

Comparing results of Model 1 with interaction effects, the model using *LN\_WTP* as dependent variable seems to outperform the one using *LN\_WTP\_KWH* when comparing Adjusted R-squares, Bayesian and Akaike's Information Criteria. Therefore, we restrict the value transfer (Section 2.5.2) to Model 1 with WTP per household and month.

For ease of interpretation, we report the marginal effects of our preferred model in Table 2.4, which is Euler's number to the power of the coefficient. The marginal effect indicates that a one percentage point increase in green electricity production increases the WTP per household (in log) by factor 1.3634 (*RE\_SHARE*) while a one percentage point increase in hydropower decreases the WTP by factor 0.9273 (*HYDRO\_SHARE*). We discriminate between hydropower and other renewables because further inspections of the data reveal that all other renewable energy sources demonstrate a positive effect on WTP. The negative effect for hydropower could be related to its large share in total renewable energy production (between 78 and 91%) in the Asian countries and in Chile.

**Table 2.4: Marginal Effects on WTP - Model 1 with Interactions**

Variable	Marginal effect on WTP per household & month (LN_WTP)
YEAR	0.5452***
RE_SHARE	1.3634***
HYDRO_SHARE	0.9273***
USA	14.2901***
METHOD_CV	2.4820**
UN_SPEC	0.0733***
Interaction ATT_KNOW	4.1671***
ATT_EDU	17.1300***
ATT_KNOWxATT_EDU	7.9617***
ATT_HH	0.3655***
ATT_INC	2.3357***
Constant	131.3569***
n=85	
Significance: *: 10%-level; **: 5%-level; ***: 1%-level	

<sup>9</sup> Estimating the models without weights has a negligible effect on the size of the estimated coefficients and the significance of variables, but reduces the explanatory power of the models significantly.



Further, our results indicate that WTP decreases over time (*YEAR*). The marginal effect of a survey conducted in the US is pronounced for WTP per household (*LN\_WTP*). However, the effect is only significant at 10%-level for WTP measured in kilowatt-hour (*LN\_WTP\_KWH*), results not shown. This is as anticipated given that the electricity consumption of an average US-household is at least twice as high as that of all other investigated countries' households, other than Finland.

In studies where information is not provided on the substitute for renewables (*UN\_SPEC*), the WTP is notably lower. We find a positive effect of contingent valuation studies (*METHOD\_CV*) on WTP per household. A likely explanation for this finding is that in our sample, choice experiments are, for the most part, based on choice sets that specify alternative energy types. In contrast, contingent valuation studies rarely provide such information. The negative marginal effect of *UN\_SPEC* decreases the expected WTP value more than the positive marginal effect of *METHOD\_CV* increases the expected WTP value.

The results for the dummies controlling for explanatory variables in the original studies (*ATT\_\**) point to significant effects for all controls. Studies that do not control for income as an explanatory variable (observations with *ATT\_INC* value zero) report significantly lower mean WTP compared to those that control for income. Controlling for education or knowledge in the original study (*ATT\_EDU*, *ATT\_KNOW*), have a large positive effect, while control variables for household characteristics (*ATT\_HH*) has a negative effect. Studies that control for both *ATT\_EDU* and *ATT\_KNOW* report higher WTPs than those that account for *ATT\_KNOW* only, but lower WTPs compared to those that capture *ATT\_EDU* only.

### **2.5.2 Value Transfer**

In the following section we present results of a value transfer based on the meta-regression function stated in equation 1 using the  $n - 1$  data splitting technique described in section 2.4.2 above. Figure 2.4 visualizes the value transfer (predicted WTP) against the elicited WTP (observed) per household per month based on the results of Model 1 with interaction effects using the full sample. Table 2.5 provides information on the quality of the value transfer (left column). The adjusted R-square of the meta-regression transfer functions is 0.77 and the mean difference between WTP and value transfer (0.51 US\$, compare Table 2.5) is not significantly different from zero. However, the large difference between the mean and the median percentage error indicates that errors might be

caused by few outliers (e.g., maximum percentage error is about 1,518%, which is more than 40 times higher the median error).

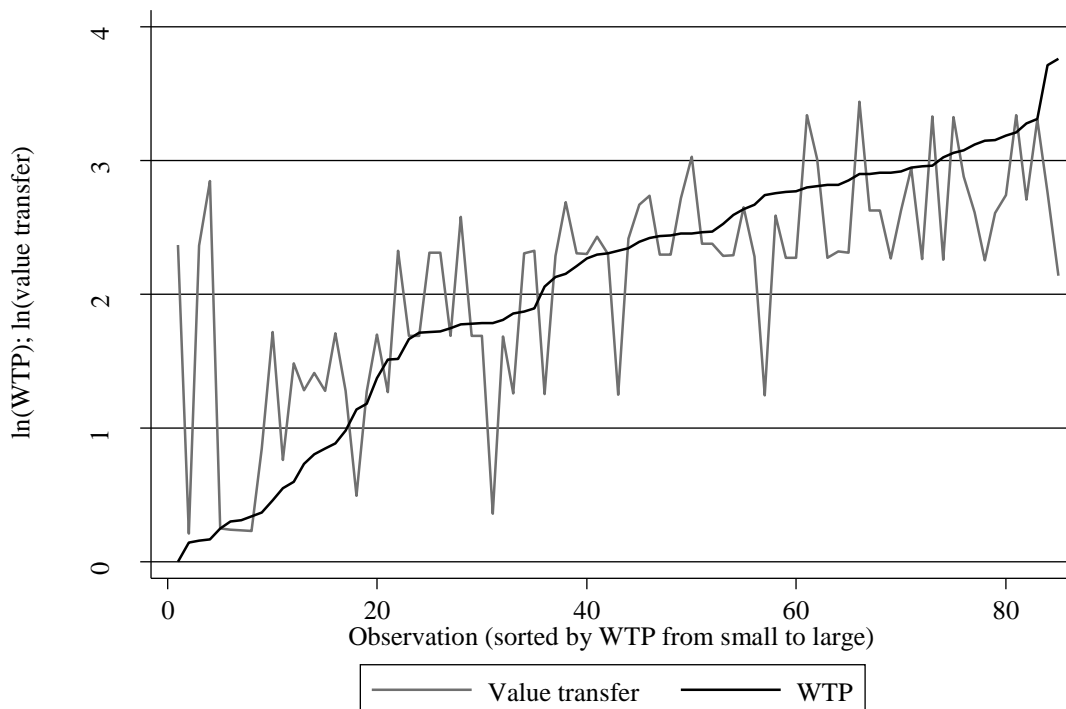
**Table 2.5: Quality of Value Transfer**

Cross validation technique		Model 1 – Interaction ( <i>LN_WTP</i> )	
Base of meta-regression transfer functions & value transfer		full sample	restricted sample
Mean adjusted R <sup>2</sup> of value transfer functions		0.7700	0.9224
Mean difference (value transfer - WTP)		0.51 US\$	-0.09 US\$
Pearson correlation coefficient		0.5902 (p=0.000)	0.8539 (p=0.000)
Absolute error	mean	5.13 US\$	2.79 US\$
	median	3.24 US\$	1.75 US\$
Percentage error	mean	88.47 %	35.97 %
	median	34.60 %	21.33 %
$\ln(y_i) = \alpha + \beta \widehat{\ln(y_i)} + \varepsilon_i$		$\alpha = 0^a$	yes
		$\beta = 1^b$	yes
Number of value transfers (observations)		85	63

<sup>a</sup> Coefficient is not significantly different from zero.

<sup>b</sup> Coefficient is not significantly different from one.

**Figure 2.4: Value Transfer Full Sample**

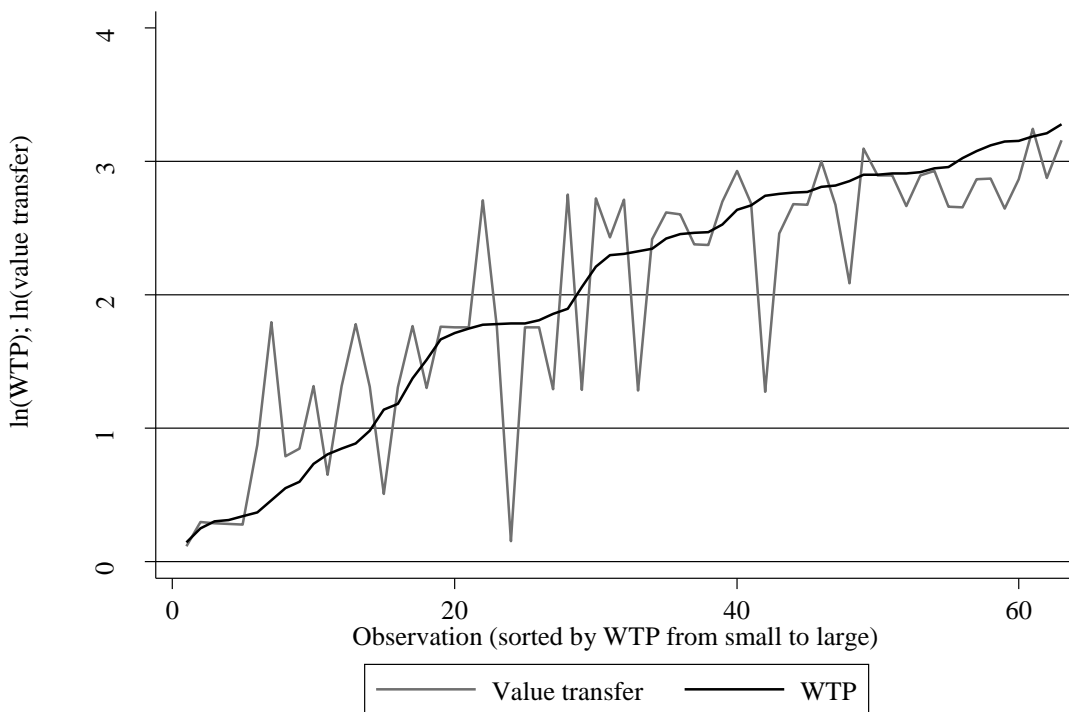


Note: Dependent variable *LN\_WTP*, Model 1 with interaction effects, N=85.

Our analysis of the outliers reveals two insights. First, we obtain twelve absolute percentage errors above 100%, seven of which correspond to WTP values that are related to an increasing share in

biomass. The positive Spearman's correlation coefficient between an absolute percentage error higher than 100% and a WTP measuring an increase in biomass, (0.3227,  $p < 0.003$ ) indicates that the meta-regression transfer function fails at estimating WTP for an increase in biomass. Second, another outlier is the WTP value provided by the Hanemann et al. (2011) study for Spain. Their WTP question is linked to a whole emission mitigating policy program. It is, therefore, likely that they overestimate WTP for an increase in green electricity only.<sup>10</sup> Omitting these outliers reduces the sample by 22 observations to 63.

**Figure 2.5: Value Transfer for Restricted Sample**



*Note: Dependent variable LN\_WTP, Model 1 with interaction effects, N=63.*

The fit of the value transfer improves significantly when re-estimating Model 1 with interactions based on the restricted sample (see Table 2.5 column on the right, and Figure 2.5). Compared to the value transfer illustrated in Figure 2.4 the new one varies less around the logarithm of the actual WTP values. The meta-regression transfer functions based on the restricted sample have a mean adjusted R-square of 0.9224. The maximum absolute value transfer error is 11.80 US\$, and the

<sup>10</sup> Their value is 8.6 times the average of all other studies for Spain (Gracia et al. 2012; Soliño et al. 2009).

maximum absolute percentage error is 296%. These error sizes seem tolerable since in 50% of the value transfers the error is below 1.75 US\$.

## **2.6 Discussion/Conclusions**

This article provides a comprehensive overview of the valuation literature on green electricity. The analysis has identified key characteristics that determine peoples' WTP for green electricity, at least for developed countries, since regional coverage in developing countries is low. Further, although we used sampling weights, we cannot guarantee that our results are not driven by WTP elicited by few studies (e.g., Borchers et al., 2007), or driven by WTP elicited in few countries (especially US and Italy).

In general, people are willing to pay for green electricity. People in Finland and the US express the largest WTPs per household and per month, while people in Chile, Italy and Germany have the highest WTP per kilowatt-hour. Countries with high electricity consumption per capita but low energy prices, such as the US and Finland, naturally state a higher WTP per household, but a low WTP per kilowatt-hour. However, WTP per kilowatt-hour is seldom reported in the literature. This could be because study participants may have a better overview of their monthly electricity expenditures than of the electricity price per kilowatt-hour.

Nevertheless, politicians lean on WTP values provided by researches so it is important to communicate WTP influencing factors, and to express WTP values in feasible units, e.g., a WTP per kilowatt-hour if politicians need advice choosing an optimal tax on electricity. That is why we recommend researches either to directly use the unit kilowatt-hour in stated preference WTP questions or to convert values per household per month by using information about household-size and electricity consumption.

Turning to the quantitative results of this article, our meta-regression shows that, in contrast to other renewable energy sources, a higher share of hydropower in a country's electricity generation reduces WTP for renewable energy. One possible explanation might be that hydropower consumes more land and has a more significant environmental impact than other types of renewables. Furthermore, people who are informed on the type of power plant to be substituted by renewables, tend to exhibit a higher WTP. This gives evidence that acceptance of renewable energies strongly depends on informing people about concrete plans, alternatives and status quo.

Significance of the dummy variables, describing the explanatory variables of study's WTP estimation, suggests that controlling for knowledge about renewables, household characteristics, income and education significantly influences WTP estimates. Ignoring these attributes in future WTP estimations might result in biased coefficients. Our analysis gives evidence that significance of other explanatory variables is caused by characteristics which are related to a specific study site; that is, they might result in another effect direction, such as regional effects, which are not caused by the region itself, but its characteristics.

Similar, studies state inconclusive WTP values for an increase in biomass. It seems that the acceptance of this renewable energy facility depends on characteristics which are not covered by our meta-regression, such as land use change. For this reason, our value transfer for an increase in biomass fails. Nevertheless, when restricting the sample to the other WTP values, we are able to predict the WTP per household per month with a median percentage error of 21% and a *MAPE* of 36%. These values are comparable to the transfer errors reported in other value transfer exercises (but not related to renewable energy; e.g., Brouwer, 2000). Further, the median absolute error of the value transfer is very small (about 1.75 US\$ per household per month). Thus, these errors might be practically acceptable to use them for policy measures.

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### 3 Second Paper: 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 CO<sub>2</sub> 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

### 3.1 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 (Gellings, 1985). 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 (Vahlenkamp et al., 2016).

Dynamic electricity tariffs incentivize consumers to shift their electricity demand (Albadi and El-Saadany, 2008). These tariffs are mainly time-of-use (TOU) tariffs with prices depending on daytime. According to Faruqui and Sergici (2010), 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 (European Commission, 2014). 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<sup>11</sup> 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. (2000) and Broberg and Persson (2016).

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 (Haucap and Pagel, 2013). So far, only Dütschke and Paetz (2013) and Schlereth et al. (2018) provided information on consumers' preferences for dynamic electricity tariffs including TOU tariffs. Dütschke and Paetz (2013), however, use a non-representative, small sample for their analysis, and Schlereth et al. (2018) focus on respondents' risk attitudes.

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<sup>11</sup> These are: Broberg and Persson (2016); Buryk et al. (2015); Daniel et al. (2018); Dütschke and Paetz (2013); Goett et al. (2000); Hall et al. (2016); Kaufmann et al. (2013); Nicolson et al. (2017); Nicolson et al. (2018); Richter and Pollitt (2018); Ruokamo et al. (2019); Schlereth et al. (2018); Stamminger and Anstett (2013).

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 3.2 provides an overview of former experiments on consumers' preferences for TOU tariffs. Section 3.3 explains our CE and our estimation method. Section 3.4 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 3.5 contains a scenario analysis estimating the potential effect of appliance control on electricity demand during peak times based on our CE results. Section 3.6 concludes and discusses our results.

### **3.2 Literature Review**

Information on consumers' acceptance of TOU tariffs is limited. Nicolson et al. (2018) 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 Nicolson et al. (2017) 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. (2000) 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. (2013) 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. (2015) 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. (2016) who conducted a non-representative opinion survey in Australia.

Focusing on the innovative tariff characteristics, Broberg and Persson (2016) 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. (2018) 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 Pollitt (2018) 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. (2019) combined in a CE dynamic tariffs with information on CO<sub>2</sub>-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 CO<sub>2</sub>-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 (2013) 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 €ct/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 €ct/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 (2013) 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. (2018) 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 (Broberg and Persson, 2016; Stamminger and Anstett, 2013). 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, 2016 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. (2005) or Franceschinis et al. (2016). 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.

### **3.3 Methodology and Data**

#### **3.3.1 Design of the Choice Experiment**

Previous research found evidence that peak time pricing decreases consumers' utility (e.g., Buryk et al., 2015). 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 3.1), 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 3.1, 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 3.1 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 (Goett et al., 2000). 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 3.1 Attributes, their description, and their levels**

Attribute	Description	Levels <sup>a</sup>
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: <u>No peak time pricing</u> , 4h/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: <u>No peak time pricing</u> , 4h/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 <sup>b</sup> , and/or freezer <sup>c</sup> , 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: <sup>a</sup> 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).

<sup>b</sup> 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.

<sup>c</sup> 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.

### 3.3.2 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 3.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 3.1). 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 3.1 presents a translated example of a choice set.

**Figure 3.1 Translated Choice Set. Tariff 3 was introduced as Status Quo**

Please have a close look at the electricity tariffs below.

Which one of these electricity tariffs would you choose?

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

I choose:

- Tariff 1
- Tariff 2
- Tariff 3

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.

### 3.3.3 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 (McFadden, 1974). 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  $\varepsilon_{nj}$ , which is distributed Type I extreme value.

As a first step, we use a conditional logit (CL) specification (McFadden, 1974) to estimate the vector of fixed marginal utilities  $\beta'$  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:

$$P_{ni} = \frac{\exp(\beta' x_{ni})}{\sum_{j \in C} \exp(\beta' x_{nj})} \quad (3.1)$$

To account for taste heterogeneity and the panel structure of the data (Revelt and Train, 1998), 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,  $\beta_n$  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  $\varepsilon_{njt}$ , 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  $\beta_n$  is given by

$$L_{njt}(\beta_n) = \frac{\exp(\beta'_n x_{njt})}{\sum_{j \in J} \exp(\beta'_n x_{njt})}. \quad (3.2)$$

We estimate these unconditional marginal utilities using the Stata add-on “mixlogit” by Hole (2007). This add-on approximates the true log likelihood function, which has no analytical form, by simulation (see e.g., Hole, 2007; Train, 2003 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  $\beta$  in the population. Using the unconditional distribution and Bayes' rule, we simulate the conditional distribution of  $\beta_n$  to estimate the ILP (see Train, 2003 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  $\beta_k$  obtained by attribute  $k$  and the marginal utility  $\beta_{discount}$  by a change in the discount:

$$WTA_k = -\frac{\beta_k}{\beta_{discount}} \quad (3.3)$$

As suggested by Bliemer and Rose (2013), 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.

### 3.3.4 Identifying Decision Strategies across Respondent Groups

Daniel et al. (2018) 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. (2018), 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.

### 3.4 Results

#### 3.4.1 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 3.2 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 3.2 Descriptive Statistics**

Characteristics	Values	Sample (N = 1398)	Germany <sup>a</sup>
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	44.67 years
Highest level of education <sup>b</sup>	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: <sup>a</sup> Own calculations based on (Statistisches Bundesamt, 2019a; 2019b) for 2017.

<sup>b</sup> For Germany: This includes population aged 15–65.

Table 3.3 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.

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.

**Table 3.3 Appliance Ownership/Times of high Electricity Consumption**

Question:		Share of respondents answering “Yes” <sup>b</sup>	
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? <sup>a</sup>	Weekdays	6 am–8 pm	93.63%
		6–10 am	23.25%
		4–8 pm	63.02%
	Weekends	6–8 am/pm	56.87%
		6 am–8 pm	91.20%
		6–10 am	17.53%
		4–8 pm	51.79%

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

<sup>b</sup> Multiple choices possible.

### 3.4.2 Estimation Results

Table 3.4 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 3.3.3). 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.

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.

**Table 3.4 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 <sup>2</sup>	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.

Before discussing the heterogeneity in WTA estimates, we present the estimated unconditional marginal WTA based on our preferred MXL specification (Table 3.5). 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 3.3). 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 3.5 Unconditional WTA in € based on MXL Results**

Attribute	Unconditional WTA			
	Marginal WTA <sup>a</sup>	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. <sup>a</sup> 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., Broberg and Persson, 2016; Ruokamo et al., 2019) found that consumers dislike a control of their electricity consumption but these studies do not differentiate between appliances. For Germany, Dütschke and Paetz (2013) discovered that households prefer an automated electricity control over a manual one.

### 3.4.3 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

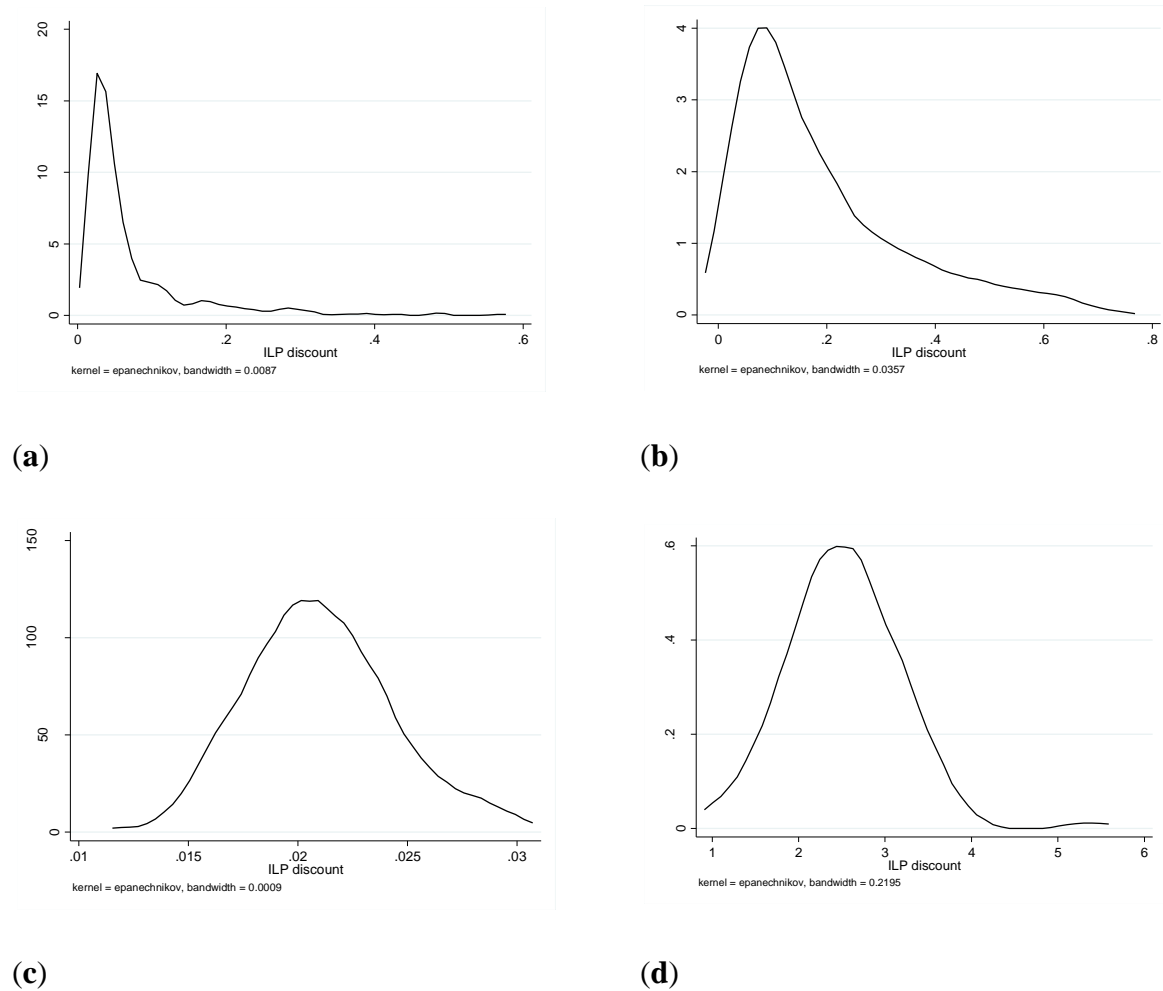
groups by their strategy, we find that the discount parameters significantly differ by decision strategy. Excluding respondents always choosing the maximum discount (strong price reaction) we discover that they exhibit discount parameter values larger than one. Next, excluding those always choosing a 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., Daniel et al., 2018).

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 3.2 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.

Visual inspection of Figure 3.2(a)–(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).

**Figure 3.2 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.**



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 3.6). For the sample as a whole, the marginal conditional WTA is about half the size of the marginal unconditional WTA (compare Table 3.5). They differ because, as showed in Section 3.3.3, 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 3.6 Median of marginal conditional WTA in € (in brackets: [5%-quantile, 95%-quantile])**

<b>Attribute</b>	<b>Sample</b> <i>N</i> = 1398 (100%)	<b>No dominant strategy</b> <i>N</i> = 476 (34.05%)	<b>Never chose the status quo</b> <i>N</i> = 506 (36.19%)	<b>Always chose the max. discount</b> <i>N</i> = 132 (9.44%)	<b>Always chose the status quo</b> <i>N</i> = 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]

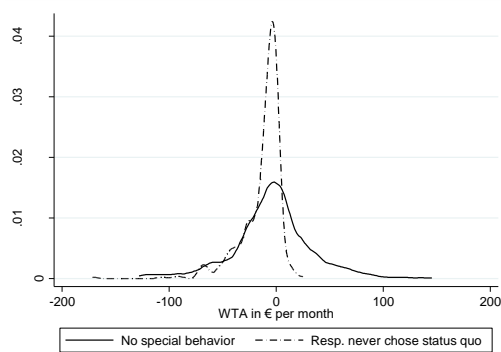
*Note: Attributes except discount are dummy coded. Baseline: Status quo, i.e., fixed rate tariff without controlling.*

Comparing marginal conditional WTA values by respondent group (Table 3.6), 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 3.2). 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.

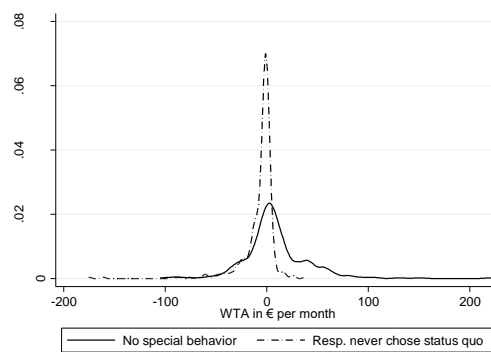
Focusing on the two groups of potential TOU tariff purchasers first, marginal WTA of respondents without dominant decision strategies is significantly higher for peak times on weekdays (Table 3.6) compared to those respondents who always choose a TOU tariff (panels (a) and (b) in Figure 3.2). This is 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.

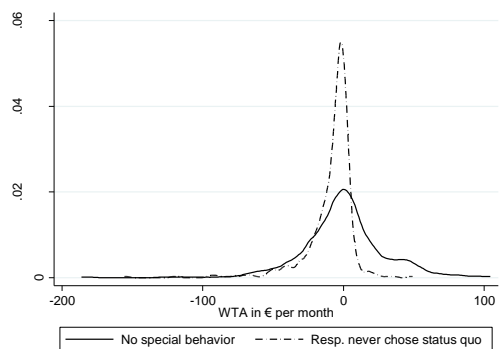
**Figure 3.3 Kernel density estimates of conditional WTA by respondent groups and appliance. Continuous line: respondents without dominant strategy. Discontinuous line: respondents who never chose the status quo but not always the maximum discount. (a) Washing machi ne; (b) dryer; (c) dish washer; (d) freezer.**



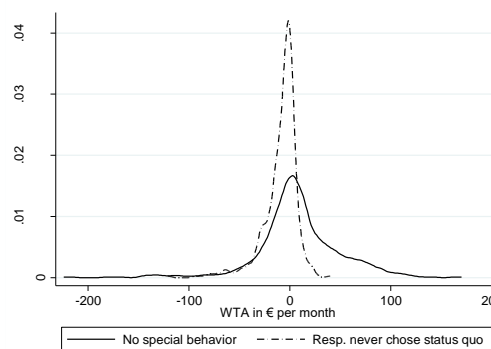
(a)



(b)



(c)



(d)

Turning to potential non-purchasers of TOU tariffs, we identify extreme WTA values (see Table 3.6). Respondents who always seek a maximum discount might exhibit a large marginal utility of discount (see panel (d) in Figure 3.2), 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 3.2). For

them the marginal WTA for peak times on weekdays (see Table 3.6) 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 3.3 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.

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.

### **3.5 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 (AG Energiebilanzen e.V., 2019). 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 3.7 provides an overview of consumers' appliance usage based on the published results (Frondel et al., 2015) 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. (2015). 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 3.7 Data used to estimate shifts in electricity demand.**

Appliance	Owners <sup>a</sup>	Consumption of appliance (in kWh per usage) <sup>b</sup>	Mean yearly usage per household <sup>c</sup>	Daily usage (in mio appliances)	Peak time usage (4 hrs a day) (in mio appliances) <sup>d</sup>
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: <sup>a</sup> Share of households in our sample in which appliance is available. <sup>b</sup> Estimated using ordinary least squares by Frondel et al. (2015). <sup>c</sup> Data based on a German household survey by Frondel et al. (2015). <sup>d</sup> We assume that the probability of using an appliance is uniformly distributed over the day.

**Table 3.8 Potential shift in electricity demand by scenarios**

Scenario <sup>a</sup>	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: <sup>a</sup> Scenarios differ by their share of TOU tariff purchasers (here: 70% in households) who accept a control of appliances.

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 3.8). 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).

### **3.6 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., Goett et al., 2000). 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. Blasch et al. (2019) 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 (Nicolson et al., 2018). 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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### **3.A Appendix**

#### **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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#### 4 Third Paper: Influence of Attitudes on Willingness to Choose Time-of-Use Electricity Tariffs in Germany. Evidence from Factor Analysis

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**Abstract:** Time-of-use (TOU) electricity tariffs are a demand side measure to ease balancing of demand and supply to cope with a rising share of renewables in a country's electricity mix. In general, consumers require compensation for accepting these tariffs. This study analyzes how attitudes drive consumers' willingness to choose a TOU tariff in Germany. To identify attitudinal profiles, I use an exploratory factor analysis on items capturing *positive* and *negative attitudes towards TOU tariffs*, *climate change awareness*, and *belief in energy saving measures*. I use these factors as predictors in an ordered logit specification to estimate consumers' stated willingness to choose a TOU tariff. Three factors are significant: *positive* and *negative attitudes towards TOU tariffs*, and *climate change awareness*. These findings highlight that decision makers who aim at balancing demand and supply through the use of TOU tariffs should focus on informing consumers about the positive impacts of these tariffs on climate change mitigation, grid stability, and possible energy savings.

**Keywords:** Time-of-use electricity tariff; Factor Analysis; Preferences; Willingness to adapt

## 4.1 Introduction

Two major issues in electricity markets are the volatility in renewable energy generation and peak demand. Both force network operators to costly redispatch in order to avoid outages when electricity demand and supply are unbalanced (Vahlenkamp et al., 2016). This holds true as long as storage technologies are not mature. Electricity tariffs with prices that reflect excess demand or supply, such as time-of-use tariffs (TOU), dynamic pricing (including real-time pricing) or critical peak time pricing, are prominent demand side measures to balance demand and supply. Given the current energy policy goals of a rising share of renewables in the electricity mix, acceptance of such measures is crucial.

In the USA, India, and 17 European countries (including Germany) time differentiated electricity tariffs were available in 2019 (IRENA, International Renewable Energy Agency, 2019). Several member states of the European Union (and Norway and UK) already offer real-time tariffs or other dynamic tariffs (Austria, Denmark, Estonia, Finland, Latvia, the Netherlands, Norway, Spain, Sweden, and UK), or critical peak pricing (Denmark, France, Latvia, and Slovenia); while 13 countries offered static TOU tariffs (ACER and CEER, 2020). These member states already implemented the EU Directive 2019/944 (The European Parliament and of the Council of the European Union, 2019) which states that consumers should financially benefit from demand response, e.g., real-time pricing. Germany has enacted this Directive into law in July 2021 by adding paragraph 41a to the Energiewirtschaftsgesetz (Deutscher Bundestag, 2021). However, until 2025 only large utility companies (more than 100,000 customers) have to offer at least one dynamic tariff to German end consumers, i.e., these tariffs need not necessarily be offered to private consumers (Bundesnetzagentur and Bundeskartellamt, 2021).

Although electricity markets globally move fast forward towards real-time pricing, TOU tariffs are neither common nor widely adopted by German consumers. According to the Federal Network Agency's most recent energy monitoring report (Bundesnetzagentur and Bundeskartellamt, 2021), only two providers offered electricity tariffs reflecting day-ahead prices in 2019. One reason is that only around 1000 smart meters had been rolled-out in private households by 2019. Further-more, usually only conservative day/night-time TOU tariffs are available, targeted at households with electric heating. Besides this, Germany is particularly interesting as policies are in place to expand the share of renewables in the gross electricity consumption from 45.4% in 2020 (Umweltbundesamt, 2021) to 65% in 2030 (Federal Ministry for the Environment, Nature

Conservation and Nuclear Safety, 2020). Thus, potential savings in CO<sub>2</sub>-emissions by increasing acceptance of TOU tariffs, or even real-time pricing, are promising (Sundt et al., 2020), since more frequent redispatch could be avoided. A choice experiment (Sundt et al., 2020) conducted nearly one year after the survey in which this paper is based on, revealed that about 70% of respondents would at least consider to choose TOU tariffs that are tied to electricity demand and supply, in Germany. Even though significant preference heterogeneity was found in this study, it was not possible to explain what drives observed heterogeneity.

Hence, this work analysis to what extent attitudes drive heterogeneity in preferences for TOU tariffs. The novelty is that, instead of including just a single behavioral aspect, 25 statements measuring attitudes towards TOU tariffs, climate change, and energy saving measures reduced to four factors are used to estimate respondents' preferences for TOU tariffs. Hereby, preference is measured by respondents' agreement with the statement about whether they would rather purchase a TOU tariff than their current tariff. Since the underlying survey was conducted in Germany, where these tariffs are still uncommon, this study is restricted to TOU tariffs with electricity prices tied to electricity demand and supply to decrease respondents' cognitive burden.

The paper is structured as follows. Section 4.2 provides a brief overview on previous studies discussing the role of selected attitudes in preferences for TOU tariffs and presents their relevance in a broader energy context. Section 4.3 describes the underlying behavioral theories and how they were acknowledged in the survey. Furthermore, it presents the econometric approach and the data set. Section 4.4 comprises the results of a factor analysis on respondents' attitudes, an estimation of respondents' willingness to choose a TOU tariff using the identified factors as explanatory variables, and insight into the predictive power of the final model. Section 4.5 discusses these results while Section 4.6 concludes and highlights implications for decision makers and further research.

## **4.2 Literature Review**

Common methods used to measure acceptance for TOU tariffs are choice experiments (e.g., Sundt et al., 2020), which is a stated preference method, and field experiments (e.g., Yang et al., 2018), which is a revealed preference method. Choice experiments usually provide an explicit hypothetical willingness to accept depending on tariffs' attributes, while field experiments aim at



observing households' actual behavior. Main finding of both branches is that preference heterogeneity exists but cannot fully be explained by common socio-demographic characteristics (e.g., Broberg and Persson, 2016). In recent research mostly one distinct behavioral aspect (e.g., risk aversion, e.g., Schlereth et al., 2018) has been added to explain heterogeneity in preferences.

These studies agree that we observe heterogeneous preferences towards consumers' acceptance of TOU tariffs (see Sundt et al., 2020 for a recent overview). As stated above, some studies identified single behavioral drivers of this heterogeneity. For example, Schlereth et al. (2018) found in their choice experiment that consumers who are more risk-averse tend to prefer time-invariant pricing. Nicolson et al. (2017) found the same for loss-averse consumers in a field experiment. In their choice experiment, Buryk et al. (2015) discovered that consumers who had been informed about environmental and system benefits of TOU and dynamic tariffs had an almost 10% lower willingness to accept (WTA) than non-informed respondents. Furthermore, males exhibit a larger WTA while those who consider it rather easy to adapt their behavior exhibit a lower WTA. Discussing with focus groups, Hall et al. (2016) found evidence that consumers' awareness of environmental benefits and their ability to shift their demand influence their willingness to choose a tariff with cost-reflective pricing. In contrast to Buryk et al. (2015), however, they find that men are more in favor for TOU tariffs than women. In addition, Yang et al. (2018) validated that knowledge about peak and off-peak pricing in respondents' region increases acceptance of TOU tariffs using personal interviews. Summarized, these studies have identified attitudinal drivers of preferences but only focus on selected aspects and do not explicitly rely on complex behavioral theories, such as the theory of planned behavior (TPB, Ajzen, 1991) or value-belief norm (VBN, Stern, 2000).

In the broader literature on energy issues, i.e., electricity prices tied to electricity consumption (e.g., Wang et al., 2012), load-restrictions (e.g., Broberg et al., 2021; Gołębiowska et al., 2020), green electricity (e.g., Bang et al., 2000; Hansla et al., 2008; Kowalska-Pyzalska, 2018; Ozaki, 2011) or energy technologies (e.g., Makki and Mosly, 2020; van Rijnsoever and Farla, 2014), attitudes were found to explain heterogeneity in preferences. Wang et al. (2012), for example, hypothesized that consumers' willingness to choose an electricity tariff with prices tied to electricity consumption is driven by elements of TPB, verified it by factor analysis, and estimated willingness to choose this tariff using an ordered logit. They found a significant impact of environmental/global warming awareness, energy saving behavior, social pressure, and electricity literacy on acceptance.

In their choice experiment, Gołębiowska et al. (2020) analyzed the impact of norms on preferences for external control of electricity consumption. They measured personal, social, and descriptive social norms using four items, and found that descriptive norms had the largest impact on preferences while personal and social had only a weak effect. Most recently, Broberg et al. (2021) showed in their split sample choice experiment that people were less likely to choose their current tariff over a tariff with load-restrictions if they were previously framed in such a way that these tariffs ease renewable energy transition.

Studies focusing on preferences for green electricity mainly rely on the TPB (e.g., Hansla et al., 2008; Kowalska-Pyzalska, 2018; Ozaki, 2011), or its predecessor reasoned action theory (e.g., Bang et al., 2000). Ozaki (2011) additionally took Roger's idea of innovation-diffusion adaption, and the VBN into account. Their results show that pro-environmental attitudes and environmental concerns increase willingness to pay (WTP) for green electricity (Bang et al., 2000; Kowalska-Pyzalska, 2018) and willingness to adapt (Ozaki, 2011). The same holds for knowledge (Bang et al., 2000; Hansla et al., 2008; Kowalska-Pyzalska, 2018; Ozaki, 2011), belief in positive consequences (Bang et al., 2000; Hansla et al., 2008), social norms (Kowalska-Pyzalska, 2018; Ozaki, 2011), and personal benefits (Ozaki, 2011). For energy technologies results are similar. Makki and Mosly (2020) performed a factor analysis on statements they collected by an extended literature research. They identified five factors describing preferences for green technologies including public awareness. Additionally, van Rijnsoever and Farla (2014) found that, again, knowledge and environmental awareness – measured using the New Environmental Paradigm (NEP, Dunlap and van Liere, 1978) scale – drives preferences.

Since former studies showed that TPB and VBN are feasible to explain preference heterogeneity in energy-related fields, it is reasonable to adapt these concepts on preferences for TOU tariffs as well. This study, therefore, fills this gap of a broader, behavioral theory-based analysis of the role of consumers' underlying attitudes as drivers of their willingness to choose a TOU tariff.

### **4.3 Methodology and Data**

#### **4.3.1 Theoretical Background**

To explore attitudes as drivers of preferences for TOU tariffs, two different but over-lapping theories that explain pro-environmental behavior (see Steg and Vlek, 2009) are mainly tested in

terms of stated willingness to choose a TOU tariff: The TPB (Ajzen, 1991), and the VBN (Stern, 2000). The relevance of common factors is, in a first step, identified through an exploratory factor analysis on statements related to consumers' expectations about the impact of TOU tariffs, their motivation to adapt their behavior, and their climate change awareness. Subsequently, these factors are used as explanatory variables in an ordered logit model to estimate consumers' stated willingness to choose a TOU tariff.

These two theories were chosen since Steg and Vlek (2009) identified three general approaches to explain pro-environmental behavior. The first approach is that consumers weight costs and benefits of their behavior. This is constituted by the TPB (Ajzen, 1991). The second approach assumes that consumer behavior is driven by moral and norms, based, e.g., on the VBN that combines environmental awareness (usually measured using the New environmental paradigm, NEP, scale; Dunlap and van Liere, 1978), beliefs and norms (Stern, 2000). The third approach explains actual buying decisions by affect. As my analysis relies on stated preferences for hypothetical TOU tariffs, this approach is not further considered. Furthermore, as highlighted in the literature review, especially TPB and VBN are promising to explain energy behavior. A combination of theories may also increase exploratory power, which has been shown by Liebe et al. (2010) to be related to forest conservation. Following their suggestions, this study combines and adjusts elements of TPB and VBN to test their explanatory power for preferences for TOU tariffs.

According to the TPB an individual's attitude towards a behavior, subjective norms, and perceived behavior control drive intention to behave (Ajzen, 1991). Related to this paper, consumers would choose a TOU tariff if they exhibit a positive attitude towards TOU tariffs, purchasing a TOU tariff would match their subjective norms, and they have the possibility to choose a TOU tariff. To be more precise, respondents form their attitude towards TOU tariffs by evaluating expected positive and negative impacts of TOU tariffs. Subjective norms cover normative beliefs (how should personal surroundings behave and how do they want one to behave?) and a feeling of moral obligation to decrease emissions ensuring mitigation of climate change. Perceived behavioral control is the extent to which respondents believe they are able to adapt a TOU tariff and how easy or difficult they find it to adapt their behavior. This includes respondents' ability to shift their electricity demand when electricity prices are high.

The VBN combines value theory, norm-activation, and environmental awareness to explain pro-environmental behavior (Stern, 2000). According to this theory, values drive one's ecological

worldview. Biospheric and altruistic values increase environmentalism, whereas egoistic values decrease it. Depending on this ecological worldview, belief in consequences of a threat is formed. Awareness of consequences results in awareness of need and responsibility to reduce a threat, and in an evaluation of ability to reduce a threat. This awareness results in action, depending on personal norms. Instead of environmental awareness, this study uses climate change awareness, which is also driven by altruism (Corner et al., 2014). Significant climate change awareness should, hence, increase a respondent's awareness of need of actions to mitigate climate change. If a respondent is able to adapt her behavior and believes that TOU tariffs mitigate climate change she should be willing to choose a TOU tariff.

This study measures climate change awareness using a 7-item scale adopted from the NEP scale (Dunlap and van Liere, 1978). The idea is that attitudes towards TOU tariffs are rather driven by climate change awareness than environmental awareness, since these tariffs rather mitigate CO<sub>2</sub>-emissions and, therefore, provide only an indirect environmental benefit. The NEP scale itself was first developed by Dunlap and van Liere (1978). Initially, they used 12 items covering statements about the environment to measure environmental awareness. In 1990, this scale was revised to a 15-item scale called the New Ecological Paradigm Scale (Dunlap et al., 2000). In empirical applications often shorter scales are used (e.g., Pierce et al., 1987).

Additionally, this study considers that instead of pure altruism, rather, a “warm glow” (Andreoni, 1990) on mitigating climate change might influence respondents' willingness to choose a TOU tariff. This would be in line with Hartmann et al. (2017) who found that warm glow has a stronger impact on pro-environmental behavior than just altruistic values. Nevertheless, altruistic values, i.e., taking actions to increase other peoples' welfare without gaining benefits yourself, increases the propensity to experience a warm glow, i.e., emotionally benefiting from altruistic actions (Andreoni, 1990). In the context of green electricity Menges et al. (2005) showed that warm glow indeed increases willingness to pay for green electricity.

#### **4.3.2 Econometric approach**

Stated attitudes are highly correlated. Therefore, estimated coefficients of a regression model would be biased because of multicollinearity. Using factors containing most information of these

stated attitudes solves this issue. Hence, an exploratory factor analysis is performed to identify relevant factors.

Lawley and Maxwell (1962) showed that a linear combination of factors can explain the  $n$  observed variables:

$$y_{ij} = z_{i1}b_{1j} + z_{i2}b_{2j} + \dots + z_{iq}b_{qj} + e_{ij} \quad (4.1)$$

where  $y_{ij}$  is the observed value of the  $i$ th individual on the  $j$ th behavioral variable,  $z_{ik}$  is the  $i$ th observation on the  $k$ th unobserved common factor, and  $b_{kj}$  is the set of linear coefficients called the factor loadings.  $e_{ij}$  is the  $j$ th variable's unique factor. Here,  $y_{ij}$  is a four-dimensional ordinal variable, hence, the analysis is based on variables' correlation matrix, i.e. a polychoric correlation matrix (Olsson, 1979).

Factors were retained using principal factors, and subsequently rotated ensuring better interpretation. Since for each variable uniqueness is clearly non-zero, an oblique promax rotation was performed. Promax is a simple rotation method that increases high factor loadings while decreasing low factor loadings and allows for correlated factors (Hendrickson and White, 1964).<sup>12</sup> Based on estimated factor loadings, respondents' individual factors are predicted.

To analyze if these retained factors explain stated *willingness to choose a TOU tariff*, an ordered logit model is estimated. An ordered logit is a generalization of logit (McCullagh, 1980) that allows for ordinal variables. It estimates the probability that an outcome for individual  $i$  falls into category  $l$  by estimating the probability that a linear function of observed variables is within a range of cutpoints:

$$\Pr(\text{outcome}_i = l) = \Pr(\kappa_{l-1} < \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_m x_{mi} + u_i \leq \kappa_l) \quad (4.2)$$

where  $\kappa_l$  is the cutpoint of category  $l$  of the *willingness to choose a TOU tariff*,  $x_{ni}$  is the  $i$ th observation on the  $n$ th explanatory variable, and  $\beta_M$  is the set of coefficients.  $u_j$  is  $i$ th individual's logistically distributed error term. The econometric analysis was performed using Stata 15.1 including the user-written add-on "polychoric" by Kolenikov and Angeles (2004).

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<sup>12</sup> Using other oblique rotation methods did not significantly change results.

### 4.3.3 Survey Design

The analysis is based on an online survey on consumers' preferences for TOU tariffs that was carried out in March and April 2016 in Germany (even though attitudes may have changed over the last five years, results of the factor analysis will be persistent and how these factors influence willingness to choose a TOU tariff is independent of individual attitudes). The final sample comprises 990 panelists of an external panel provider (Consumerfieldwork GmbH) who incentivize their members by paying them less than 3€ per completed survey. This panel provider drew a random sample of their panel members and invited them via email to answer the survey. Quota sampling was conducted to ensure sample's representativeness for Germany in terms of age groups and gender. Northern Germany (Northern Germany consists of the following federal states: Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, and Mecklenburg-Western-Pomerania) is oversampled (50% instead of 18%) since it is disproportionately affected by the expansion of renewable energies. One shortcoming of this oversample is that the small sample size did not allow for the addition of other quotas, such as those related to housing characteristics. Respondents were at least 18 years old.

The survey (see Appendix 4.B) included four parts: (1) screen-out questions; (2) electricity consumption related questions; (3) attitudinal questions; and (4) additional sociodemographic questions. The first part comprised questions about age, gender, and state of residence to enable a representative sample. The second part involved general questions about household's electricity consumption, their electric appliances affecting electricity consumption (e.g., electric heating, and private microgeneration), and their current electricity tariff.

Before the attitudinal questions in part three, respondents were given information on TOU tariffs (see Appendix 4.B; question 11). These were described as a measure to balance electricity demand and supply; i.e., a tariff with a high electricity price when demand exceeds supply and vice versa. Additionally, it was mentioned that – at least in Germany – redispatch is a costly and CO<sub>2</sub>-intensive measure to handle excess demand. Furthermore, respondents were reminded that they could actually lower their electricity bill if they shifted their electricity demand. Initially, respondents were randomly assigned to two treatments that differed by the reasoning of TOU tariffs. TOU tariffs were described as a measure to decrease electricity demand either during peak demand or when renewable energy supply is low. Since these treatments have no effect on the results of this analysis (insignificance of the treatment variable), they are treated as one sample.

Part three focused on behavioral aspects and respondents' stated willingness to choose a TOU tariff as described in the previous paragraph (see Section 4.4.1 for summary statistics). At first, respondents provided information on their current electricity tariffs and drivers for their decision-making. Subsequently, respondents revealed their values, attitudes, and subjective norms based on the TPB and the VBN with regard to TOU tariffs (i.e., their climate change awareness; their evaluation of electricity saving measures; their perception of TOU tariff's impacts; and their motivation to choose a TOU tariff; see Appendix 4.B, questions 16-19). Each statement was measured using a four-item response scale. On these 25 statements in questions 16 to 19, the exploratory factor analysis was performed; subsequently an ordered logit was used to estimate respondents stated willingness to choose a TOU tariff (first item of question 19) using the identified factors as explanatory variable. The third part concluded with a self-assessment of respondents' willingness to take risk using a 10-item Likert scale ranging from “absolutely not willing to take risk” to “absolutely willing to take risk” (see Appendix 4.B, question 20). The final section contained general sociodemographic questions, such as net household income, educational attainment, and employment status.

## **4.4 Results**

### **4.4.1 Descriptive Sample Statistics**

Table 4.1 provides an overview of the sample. Note, that it is representative regarding age and gender for the target population. As usual for online surveys, respondents with a higher education level (12 to 13 years of schooling) are overrepresented. Median income, employment status and household size are similar to the target population.

Turning to respondents' current electricity tariffs (Table 4.2), about 20.5% have a tariff that consists of 100% renewable electricity. Only about 9% already have a TOU tariff. In Germany, these tariffs are currently designed to incur low prices at night and higher prices otherwise. This indicates that there is a high potential for shifting electricity demand in Germany. Note that, market shares of electricity tariffs are not available for Germany. However, stakeholders agree that shares of TOU tariffs, smart home tariffs and special tariffs for heat pump/night storage heating are very low. Furthermore, the market share in electricity sales of 100% renewable energy tariffs amounted to 23.1% in 2016 (Bundesnetzagentur and Bundeskartellamt, 2016). Assuming that average

electricity consumption is independent of electricity tariff characteristics, the share of 100% renewable tariffs in this sample seems reasonable.

**Table 4.1: Sociodemographic Characteristics**

Characteristic	Levels	Sample		Germany <sup>a</sup>
		Number	Share	
Sample		990	100%	82.5 Million
Gender	Female	504	50.91%	50.68%
	Male	486	49.09%	49.32%
Age (18 y and older)	Mean	49.29		50.61
	Median	50		51
Household size	Mean	2.21		2.01
Household net income (in categories)	Median category	2000€ -2499€		2000€ -2599€
	<i>Missing</i>	123	12.42%	
Education (in years)	Low (Up to 9 y)	121	12.22%	35.05%
	Middle (10 y)	357	36.06%	29.44%
	High (12 to 13 y)	486	49.09%	30.77%
	<i>Missing/not applicable</i>	26	2.63%	4.75%
Employment	Full-time	337	34.04%	32.06%
	Part-time	131	13.23%	12.83%
	Retired	281	28.38%	22.92%
	Other	226	22.83%	31.71%
	<i>Missing</i>	15	1.52%	0.12%

<sup>a</sup> Data source: Statistisches Bundesamt (2021), own calculations. Note that mean and median age is calculated for population 18 years and older.

**Table 4.2: Characteristics of Current Electricity Tariff**

Tariff attributes	Levels	Share
100% Renewables	Yes	20.51%
	No	57.98%
	<i>Don't know</i>	21.52%
Time-of-use tariff	Yes	8.59%
	No	73.03%
	<i>Don't know</i>	18.38%
Tariff for heat pump / night storage heater	Yes	6.26%
	No	77.47%
	<i>Don't know</i>	16.26%
Smart home tariff	Yes	8.79%
	No	67.07%
	<i>Don't know</i>	24.14%

Note: Multiple answers possible. See Appendix 4.B, question 9 for details.



Tables 4.3 to 4.6 provide information on respondents' attitudes later used for the exploratory factor analysis. Table 4.3 summarizes motivational aspects, i.e., subjective norms (TPB), values (VBN) and perceived behavior control (TPB). Note that the first item *stated willingness to choose a TOU tariff* is the dependent variable in the regression analysis. On average, respondents would rather not choose a TOU tariff instead of their current tariff. This could be related to the fact that they are unsure whether they can adjust their electricity consumption. Surprisingly, respondents disagree that their social environment would support their decision in favor of a TOU tariff. However, on average, respondents expect others to behave in an environmentally friendly way and care about others (last statement).

**Table 4.3: Statements Measuring Motivation and Social Norms**

<b>Statement</b>	<b>Mean (Std.dev.)</b>	<b>Mode</b>
I would like to choose a TOU tariff rather than my current electricity tariff <sup>a</sup>	2.29 (0.86)	2
I am doing enough already to save energy; thus, I do not additionally need to choose an electricity tariff with variable electricity prices	2.68 (0.82)	3
My social environment would like it if I would choose TOU tariff	2.36 (0.85)	2
I expect other people around me to behave in an environmentally friendly way	3.13 (0.73)	3
For me, it would be easy to limit my electricity consumption in case I am at home when electricity prices are high	2.52 (0.90)	3
Purchasing such an electricity tariff gives me a warm glow to contribute to climate protection	2.58 (0.87)	3
I do not want others to suffer from the impacts of climate change	3.24 (0.68)	3

*Note: Variables measured using a 4-item scale: 1 fully disagree – 2 rather disagree – 3 rather agree – 4 fully agree. See Appendix 4.B, question 19 for details.*

<sup>a</sup> *This statement is referred to as (stated) willingness to choose a TOU tariff.*

To capture awareness of the need for and consequences of TOU tariffs (VBN), as well as more general attitudes towards them (TPB), respondents were asked to rate their expectations regarding the potential impact of TOU tariffs (Table 4.4). Respondents on average do not clearly agree or disagree with these statements. This might relate to their inexperience with TOU tariffs. Nevertheless, respondents clearly expect increasing monthly electricity costs and increasing electricity providers' profits by TOU tariffs.

**Table 4.4: Perceived Impacts of TOU tariffs with Prices Related to Electricity Demand and Supply**

<b>Impact</b>	<b>Mean (Std.dev.)</b>	<b>Mode</b>
Ensures that power outages will continue to be rare in Germany	2.79 (0.78)	3
Mitigates CO <sub>2</sub> -emissions	2.62 (0.82)	3
Increases monthly electricity costs	2.95 (0.79)	3
Increases electricity providers' profits	3.08 (0.79)	3
Will lead to electricity shortages during certain times	2.54 (0.86)	3
Decreases electricity consumption	2.44 (0.81)	2

*Note: Variables measured using a 4-item scale: 1 fully disagree – 2 rather disagree – 3 rather agree – 4 fully agree. See Appendix 4.B, question 18 for details.*

In terms of perception of the feasibility of electricity-saving measures, Table 4.5 provides first insights into respondents' attitudes towards TOU tariffs (related to TPB). On average respondents are not sure if TOU tariffs will save any electricity at all. This is understandable since the main objective of TOU tariffs is to shift electricity demand, and not to lower it. However, respondents do not believe that an increase in average electricity prices would reduce electricity demand. This may indicate that respondents are not willing to reduce their electricity consumption in general.

**Table 4.5: Feasibility of Electricity Saving Measures**

<b>Measure</b>	<b>Mean (Std.dev.)</b>	<b>Mode</b>
Purchasing a TOU tariff <sup>a</sup>	2.48 (0.87)	3
Switching off electrical appliances instead of using stand-by	3.53 (0.65)	4
Increasing average electricity prices	1.88 (0.76)	2
Switching off lights when leaving a room	3.51 (0.69)	4
Buying electrical appliances with low electricity consumption	3.57 (0.64)	4
Replacing old light bulbs or halogen bulbs by electricity saving alternatives	3.36 (0.77)	4

*Note: Variables measured using a 4-item scale: 1 not feasible – 2 somewhat not feasible – 3 somewhat feasible – 4 feasible.*

<sup>a</sup> *Description varies by treatment (see Appendix 4.B, question 17 for details).*

Table 4.6 summarizes respondents' climate change awareness. Note that on average, climate change is perceived as a real, serious and human-made problem. Respondents, on average, rather disagree with the statements that climate change can be handled without limiting our lifestyles and that media exaggerates climate change.

Compared to the results of the European Social Survey on attitudes towards climate change (Poortinga et al., 2018) in 2016–2017 respondents are somewhat less sure that climate changes (91.3% compared to 95.4%; and agree less that humans are responsible for this change (88.5% compared to 94.8%). The latter difference in particular may result from differences in the

statements that should be evaluated. While the European Social Survey asks if “climate change [is] at least partially caused by humans”, this weakening is not present in the statement in this survey. It is even more difficult to compare the statement that “climate change impacts will be bad” (77.4% agree) with “climate change is a serious problem” (90.1% at least agree). Note that a problem might be evaluated as serious without having bad impacts.

**Table 4.6: Climate Change Awareness**

<b>Statement</b>	<b>Mean (Std.dev.)</b>	<b>Mode</b>
Climate change is a serious problem	3.47 (0.73)	4
My personal actions influence climate change	2.97 (0.81)	3
People are responsible for climate change	3.33 (0.74)	4
There will be a solution to climate change without limiting our lifestyle	2.15 (0.84)	2
Scientific predictions regarding climate change are trustworthy	2.92 (0.72)	3
I am sure that climate change is happening	3.37 (0.69)	4
Media exaggerates climate change	2.20 (0.89)	2

*Note: Variables measured using a 4-item scale: 1 fully disagree – 2 rather disagree – 3 rather agree – 4 fully agree. See Appendix 4.B, question 16 for details.*

## **4.4.2 Empirical Analysis**

### **4.4.2.1 Results of the Factor Analysis**

The exploratory factor analysis using the 25 attitudinal statements introduced in Tables 4.3-4.6 results in four factors that exhibit an eigenvalue larger than one (see Appendix 4.A., Table 4.9 for detailed results). They explain 99% of the variation in the items based on the Kaiser Criteria (Kaiser, 1960). The fifth factor does not provide much additional information; hence, this factor and the following are excluded from further analyses. The overall Kaiser-Meyer-Olkin criteria of sampling adequacy (Kaiser, 1974) is meritorious (0.8753).

Table 4.7 presents the rotated factor loadings larger than 0.3, and items' uniqueness, i.e., how much of each item's variance is not explained by factors. Note that each item only belongs to a single factor. Some items have a uniqueness larger than 0.6 or even 0.8 (expecting electricity shortage) indicating that these items are less well explained by the factors. Since this study does not aim to find the best factor but a feasible predictor, these items remain in the present analysis.

**Table 4.7: Rotated Factors**

<b>Factor</b>	<b>Variable</b>	<b>Factor Loading</b>	<b>Uniqueness</b>
Positive Attitude towards TOU Tariffs	Purchasing a TOU tariff is a feasible measure to save electricity	0.6024	0.5177
	Increasing average electricity prices	0.4234	0.8128
	TOU tariffs ensure that power outages will continue to be rare in Germany	0.4916	0.7265
	TOU tariffs mitigate CO <sub>2</sub> -emissions	0.6883	0.5080
	TOU tariffs decrease electricity consumption	0.7595	0.4543
	My social environment would like it if I would choose TOU tariff	0.7084	0.4404
	I expect other people around me to behave environmentally friendly	0.3234	0.5892
	For me, it would be easy to limit my electricity consumption in case I am at home when electricity prices are high	0.6392	0.5862
	Purchasing such an electricity tariff gives me a warm glow to contribute to climate protection	0.7665	0.2996
Negative Attitude towards TOU tariffs	TOU tariffs increase monthly electricity costs	0.6685	0.4858
	TOU tariffs increase electricity providers' profits	0.6473	0.5001
	TOU tariffs will lead to electricity shortages during certain times	0.4109	0.8047
	I am doing enough already to save energy; thus, I do not additionally need to choose an electricity tariff with variable electricity prices	0.4258	0.6756
Climate Change Awareness	Climate change is a serious problem	0.8472	0.2532
	My personal actions influence climate change	0.6589	0.4961
	People are responsible for climate change	0.7459	0.4317
	There will be a solution to climate change without limiting our lifestyle	-0.5342	0.6694
	Scientific predictions regarding climate change are trustworthy	0.6909	0.4829
	I am sure that climate change is happening	0.8280	0.3712
	Media exaggerates climate change	-0.7546	0.4074
	I do not want others to suffer from the impacts of climate change	0.4318	0.6086
Belief in Energy Saving Measures	Switching off electrical appliances instead of using stand-by	0.6944	0.5475
	Switching off lights when leaving a room	0.7149	0.4919
	Buying electrical appliances with low electricity consumption	0.7498	0.4201
	Replacing old light bulbs or halogen bulbs by electricity saving alternatives	0.6543	0.5402

Note: Factor loadings are presented if they are larger 0.3. Sample Size=990.

The first factor named *Positive Attitude towards TOU Tariffs* comprises positive statements on TOU tariffs. It relates to the main elements of the TPB and parts of the VBN, such as awareness of consequences and need. Attitude in the sense of TPB includes its feasibility as an electricity saving measure as well as its positive effects. Additionally, *Positive Attitude* includes respondents' subjective norms, their perceived behavioral control, and their sense of 'warm glow'. Its counterpart, *Negative Attitude towards TOU Tariffs*, measures respondents' expectations of negative impacts and their belief that they are already doing enough to save energy. The factor *Climate Change Awareness* includes the items of the climate change awareness scale plus altruism;

hence, it captures values in the sense of the VBN. The last factor measures respondents' *Belief in Energy Saving Measures* in general.

Using all factor loadings (including those below 0.3) factors are predicted for each respondent. Factor means are standardized to zero. Standard deviation ranges from 0.81 (*Negative Attitude*) to 0.90 (*Positive Attitude*). T-tests on differences in factor means suggest that females exhibit a significantly more *Positive Attitude* (5%-level) and less *Negative Attitude towards TOU Tariffs* (1%-level). Furthermore, they are more *Climate Change Aware* (1%-level) and have a stronger *Belief in Energy Saving Measures* (1%-level). Moreover, I found regional differences. Respondents living in northern Germany exhibit a more *Positive* (5%-level) and less *Negative Attitude towards TOU Tariffs* (5%-level) as well as a higher *Climate Change Awareness* (5%-level) compared to respondents from other parts of Germany. One possible explanation could be that a lot of renewable energy is generated in northern Germany. Further *t*-tests show that respondents with a 100% renewables tariff are more *Climate Change Aware* (5%-level). Income does not play a significant role in attitude formation.

#### **4.4.2.2 Results of the Regression Analysis**

This aimed to analyze if behavioral attitudes, i.e., the identified factors, explain if respondents are more willing to choose a TOU tariff than their current tariff (Table 4.8). Note that factors' coefficients relate to effects that deviate from mean attitudes.

The first model (Model 1) includes only the above factors as explanatory variables. A more *Positive* than average *Attitude towards TOU Tariffs* has a large positive significant effect on willingness to choose a TOU tariff and explains most of the variation; *Negative Attitude* has a small negative significant effect. *Climate Change Awareness* and *Belief in Energy Saving Measures* have no significant effect in this model. However, using principal factors in a factor analysis allows for correlated factors. Indeed, *Climate Change Awareness* and *Belief in Energy Saving Measures* are significantly (1%-level) correlated (Spearman's rho = 0.4758). Therefore, Model 2 excludes *Belief in Energy Saving Measures*, and Model 3 excludes *Climate Change Awareness* to check if their effects overlap. In Model 2 the effect of *Climate Change Awareness* is small and negative, and significant only at the 10%-level. This indicates that respondents who are more climate change

conscious are more likely to believe that energy should be saved in general, rather than just shifting demand.

Model 4 extends Model 2 such that it includes additional covariates, which are not correlated with any factor. Respondents who consider themselves as less willing to take risks have a higher willingness to choose a TOU tariff. Furthermore, respondents who are already planning to change their electricity tariff are more likely to be in favor of TOU tariffs. The effect of age is inverted U-shaped; middle-aged respondents are more likely to choose a TOU tariff. Furthermore, a larger household size also has a positive effect. A possible explanation could be that daily routine of larger households is more structured and is easier to adjust.

**Table 4.8: Ordered Logit Models to Predict Willingness to Choose a TOU Tariff**

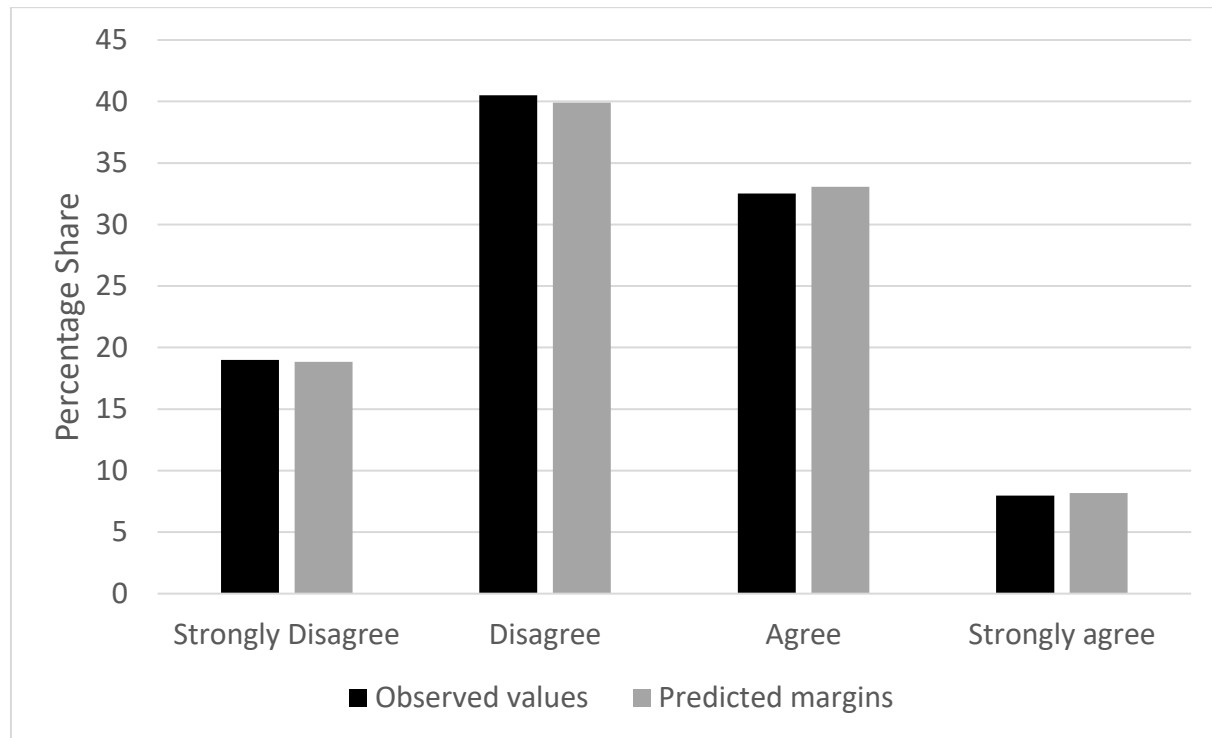
Variable	Model 1		Model 2		Model 3		Model 4	
	Coeff. (Std.err.)	p-Value	Coeff. (Std.err.)	p-Value	Coeff. (Std.err.)	p-Value	Coeff. (Std.err.)	p-Value
Explanatory variables								
Positive Attitude towards TOU Tariffs	1.9387 *** (0.1139)	0.000	1.9408 *** (0.1138)	0.000	1.9029 *** (0.1121)	0.000	1.9144 *** (0.1182)	0.000
Negative Attitude towards TOU Tariffs	- 0.4332 *** (0.0936)	0.000	- 0.4412 *** (0.0922)	0.000	- 0.4217 *** (0.0920)	0.000	- 0.4637 *** (0.0930)	0.000
Climate Change Awareness	- 0.1089 (0.0961)	0.257	- 0.1457 * (0.0833)	0.080			- 0.1679 * (0.0867)	0.053
Belief in Energy Saving Measures	- 0.0845 (0.0994)	0.395			- 0.1294 (0.0870)	0.137		
1—Fully risk averse to 10—Fully risk seeking							0.0822 ** (0.0325)	0.011
Dummy = 1 if household plans to switch tariff							0.4660 *** (0.1283)	0.000
Dummy = 1 if household has a TOU / smart home tariff							0.4214 *** (0.1597)	0.008
Dummy = 1 if respondent believes that the survey results influence future decisions							0.2438 * (0.1445)	0.092
Age							0.0532 ** (0.0244)	0.029
Age squared							- 0.0005 ** (0.0003)	0.029
Household size							0.1290 ** (0.0603)	0.032
Cutpoints								
“rather disagree”	- 2.2219 (0.1223)		- 2.2193 (0.1219)		- 2.2205 (0.1224)		0.0409 (0.5896)	
“rather agree”	0.5752 (0.0773)		0.5725 (0.0771)		0.5752 (0.0772)		2.9260 (0.5938)	
“fully agree”	3.5031 (0.1486)		3.5041 (0.1490)		3.4975 (0.1483)		5.9624 (0.6293)	
Goodness of fit								
Log pseudolikelihood		- 942.7650		- 943.2391		- 943.5082		- 919.4592
Pseudo-R <sup>2</sup>		0.2373		0.2369		0.2367		0.2562

Note: Sample size = 990. Stars indicating significance at 1%-level: \*\*\*; at 5%-level: \*\*; at 10%-level: \*. Robust standard errors.

To evaluate the predictive power of Model 4, its results are used to predict the margins of respondents' willingness to choose a TOU tariff. Figure 4.1 illustrates the distribution of the

observed values against the predicted margins. Overall, Model 4 predicts the distribution well. On the individual level the prediction corresponds to the actual *willingness to choose a TOU tariff* in only 60% of cases but the deviation is greater than one category in only 3.5% of cases.

**Figure 4.1: Willingness to Choose TOU tariffs**



Note: Sample size=990.

#### 4.5 Discussion

This study investigates the influence of behavioral attitudes on consumers' willingness to choose TOU tariffs. An exploratory factor analysis identifies four factors that load on those attitudes. A first factor measures respondents' *Positive Attitude towards TOU Tariffs* related to the TPB and VBN and warm glow. Its counterpart comprises respondents' *Negative Attitude towards TOU Tariffs* based on their perceived negative impacts. A third factor measures *Climate Change Awareness* based on a scale dealing with statements about climate change adopted from the NEP-scale and altruism. A fourth factor covers general *Belief in Energy Saving Measures*. Remarkably, women tend to have a more *Positive* and less *Negative Attitude towards TOU Tariffs* and are more *Climate Change Aware*. The same holds for respondents living in Northern Germany who are more experienced with renewable energy facilities.

An ensuing ordered logit estimation using these factors to explain stated willingness to choose TOU tariffs identifies three significant factors: *Positive* and *Negative Attitude to-wards TOU Tariffs* as well as *Climate Change Awareness*. While a more *Positive* and less *Negative Attitude towards TOU Tariffs* unsurprisingly increases the probability that respondents choose a TOU tariff, a higher *Climate Change Awareness* slightly decreases that probability. For the latter, one possible explanation could be that more climate-conscious respondents prefer a general reduction in energy consumption rather than just a shift in demand. This issue has also been reported by focus groups discussing cost-reflective electricity tariffs in Australia (Hall et al., 2016). Furthermore, Hall et al. (2016) found that women are less in favor of TOU tariffs, which may be due to women being more climate change aware. However, the effect of *Climate Change Awareness* is small and only significant at the 10%-level. In addition, I find that women have a more *Positive* and less *Negative Attitude towards TOU Tariffs*. This indicates that these differences in attitudes could explain lower WTA values of women for TOU tariffs as estimated in choice experiments by, for example, Buryk et al. (2015). Nonetheless, it appears that the gender effect is more indirectly driven by differences in attitudes.

Adding additional covariates to the model results in further insights of drivers for respondents' willingness to purchase a TOU tariff. Respondents are more likely to choose these tariffs if they are more willing to take risk. This is in line with the results of the choice experiment by Schlereth et al. (2018) who find that German consumers who are risk-averse prefer time invariant pricing. Furthermore, I observed that respondents who have experience with TOU or smart home tariffs are more likely to adopt TOU tariffs. Also, respondents who plan to change their tariff are more likely to be in favor of TOU tariffs. Not surprisingly, middle-aged respondents are more in favor of TOU tariffs, while older and younger ones are more critical. This finding is similar to Yang et al. (2018) where elderly Chinese people were less likely to state they are willing to choose a TOU tariff. However, they assumed a linear relationship of age instead of a U-shaped one. It is noteworthy that larger households favor TOU tariffs. This finding already surprised Nicolson et al. (2017) since they expected that households with children would exhibit a lower willingness to switch to a TOU tariff. However, I think that larger households might be better organized than smaller ones, making it easier for them to adjust. For example, large households can shift their laundry from one day to the next, while single households have less laundry overall, so their ability to shift laundry is lower.



Preferences for TOU tariffs might additionally differ by total electricity consumption, housing characteristics or the life-cycle of a household. Although electricity consumption was queried (Appendix 4.B, question 8), a majority of the values did not pass a plausibility test. Therefore, it was not possible to take this variable into account. Housing characteristics were only included to a small extent in the questionnaire, i.e., if a household has electric heating, and if their house has a solar panel/photovoltaic (Appendix 4.B, questions 4 to 6). These variables were insignificant, thus, excluded from further analysis. One reason might be that households with electric heating are more likely to already have a smart home or TOU tariff (31% instead of 14%). The life-cycle of a household has been approximated by respondents' employment status (Appendix 4.B, question 26). However, this variable has not been proven as feasible in this analysis. This might be due to the fact that respondents were already queried to state their perceived possibility to adapt their electricity consumption (Appendix 4.B, question 19). Thus, this life-cycle effect has already been captured by this statement that is captured in the factor Positive Attitude towards TOU tariffs.

It is interesting to note that income is an insignificant factor. Electricity is a basic need and consumption is rather independent of income. Since quality does not differ significantly, it is primarily prices per kWh and, as this study suggests, intrinsic motivation, that drive consumer decisions. Decision makers who want to promote TOU tariffs could benefit from these findings by highlighting positive impacts of TOU tariffs and addressing preconceptions about TOU tariffs and their benefits to utility companies. Buryk et al. (2015) showed that information about system and environmental benefits of TOU tariffs reduce compensation required for acceptance of TOU tariffs. However, decision makers should be aware that this moral suasion does not necessarily lead to significant habit formation. In a field experiment, Ito et al. (2018) demonstrated that financial incentives are more persistent. They observed that consumers who were nudged by moral suasion to shift their electricity demand to off-peak hours showed less persistent behavior change than consumers who were nudged by financial incentives.

#### **4.6 Conclusion**

This study shows that TPB and VBN explain a significant share of preference heterogeneity for TOU tariffs. While attitudes towards these tariffs (respectively awareness of consequences, need, and responsibility) and warm glow clearly influence preferences; climate change awareness including altruism have no distinct effect. Even though these attitudes might vary over time (e.g.,

recent flood events in Germany might increase climate change awareness) and countries, I expect their influence to remain persistent in size. Furthermore, the results of the factor analysis should not change when respondents' attitudes change, because the individual factors are determined based on the correlations between the statements. However, this survey has to be repeated for Germany, and similar analysis has to be undertaken for other countries in order to test this hypothesis.

Excluding some of these attitudes or a measure for risk behavior of respondents would probably lead to systematic biases in future analyses. For example, this study shows that gender effects, which are inconclusive over studies, might result from differences in attitudes. This might be due to the fact that women have a more *Positive* and less *Negative Attitude towards TOU Tariffs*, that increases willingness to choose a TOU tariff, while they exhibit a higher *Climate Change Awareness* that rather decreases this willingness. Since these results are limited to TOU tariffs, future research should test if the identified factors, and therefore attitudes, influence preferences for dynamic electricity tariffs on a similar level.

An important limitation constitutes that this study has not tested to what extent financial incentives influence consumers' willingness to choose a TOU tariff. Respondents were only informed that, if they adapt their electricity consumption to a TOU tariff properly (see Appendix 4.B, question 11), they would be able to decrease their electricity bill. Further research should, therefore, take the attitudinal statements presented in this survey into account when estimating willingness to accept TOU tariffs.

Since attitudes significantly influence preferences for TOU tariffs, policy makers should clearly communicate environmental and potential financial benefits to consumers, and at the same time eliminate prejudices. Nevertheless, in the case of Germany, unavailability of TOU and dynamic tariffs remains the core issue. The latest amendment of the *Energiewirtschaftsgesetz* (Deutscher Bundestag, 2021) that forces utility companies to offer at least one TOU tariff or even dynamic tariff to end consumers will not necessarily increase supply to private households. A major obstacle is that smart meter roll-out in Germany (i.e., installation of a digital meter plus a communication device, which is necessary to enable dynamic tariffs) is only mandatory for end consumers exceeding an electricity consumption of 6000 kWh per year (e.g., households with a heat pump or an electric vehicle) or prosumers with an installed capacity of at least 7 kW (Deutscher Bundestag, 2016). All other households will only receive digital meters. German policy makers should, therefore, think over their strategy of smart-meter roll-out if they want to increase adoption of

modern TOU tariffs or dynamic tariffs since, even though, policy makers would succeed in increasing positive attitudes towards TOU tariffs, households would need to actively demand these additional communication de-vices. This issue further hinders households from choosing a TOU tariff.

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**Institutional Review Board Statement:** An ethical review of this study was waived because it was conducted via an external panel provider (Consumerfieldwork GmbH) who both reviewed the questionnaire and ensured the anonymity and data protection of the participants. Participation was voluntary and could be terminated at any time. Participants could skip individual questions and were not exposed to psychological or physical risks at any time.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** The data used in this study include sensitive respondent information. Respondents have been assured that their individual data will be kept confidential and will be explicitly available only to academics. I am happy to share these data with other researchers, provided that such a request is explicitly limited to academic purposes.

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#### 4.A Appendix A

**Table 4.9 Results unrotated factor analysis**

<b>Factor</b>	<b>Eigenvalue</b>	<b>Difference</b>	<b>Proportion</b>	<b>Cumulative</b>
Factor 1: <i>Climate Change Awareness</i>	6.3799	3.4904	0.5317	0.5317
Factor 2: <i>Positive Attitude towards TOU tariffs</i>	2.8895	1.4132	0.2408	0.7726
Factor 3 <i>Belief in Energy Saving Measures</i>	1.4763	0.3434	0.1230	0.8956
Factor 4 <i>Negative Attitudes towards TOU tariffs</i>	1.1329	0.5870	0.0944	0.9900
Factor 5	0.5459	0.1243	0.0455	1.0355
...	...	...	...	...

*Note: Sample size = 990; Method: principal factors on items' polychoric correlation matrix.*

#### 4.B Appendix B

##### **Translated Questionnaire (original in German)**

1. Please indicate your gender:

- Female
- Male

2. How old are you?

3. Which state do you live in?

- Baden-Württemberg
- Bavaria
- Berlin
- Brandenburg
- Hamburg
- Hessen

- Mecklenburg-Western-Pomerania
  - Lower Saxony
  - North Rhine-Westphalia
  - Rhineland-Palatine
  - Saarland
  - Saxony
  - Saxony-Anhalt
  - Schleswig-Holstein
  - Thuringia
  - I do not live in Germany
4. Do you use one or several of following electricity using appliances to heat water? (Multiple answers allowed)
- Boiler
  - Instantaneous water heater
  - Electricity is not used to heat water
5. Do you heat with electricity?
- Exclusively/Mostly
  - Sometimes (e.g., heating fan during winter)
  - Never
  - Don't know
6. Is there a photovoltaic/solar system installed on the house where you live in?
- Yes
  - No
  - Don't know
7. How do you estimate the electricity consumption of your household compared to other households? Please, consider households of the same size.
- Much lower
  - Lower
  - Similar

- Higher
  - Much higher
8. Please, estimate how much electricity your household consumed during last year? You can either state your monthly or yearly electricity consumption.
- Monthly:
  - Yearly:
  - Don't know
9. Electricity tariffs may have different characteristics. Which of the following characteristics does your current electricity tariff have? (Multiple answers allowed; Options: yes, no, don't know)
- 100% electricity from renewable energies
  - Electricity price dependent of time of day and day of the week
  - Special tariff for heat pump or night storage heating
  - Regional origin of electricity from renewable energy is known
  - Smart home tariff
10. Which of the following reasons influences your decision for your electricity tariff? (Multiple answers allowed; Options: yes, no, don't know)
- Comprehensibility of tariff description
  - Share of renewable energy
  - Origin of electricity (e.g., regional)
  - Electricity price per kilowatt-hour
  - Other reasons, namely:

11. Information on TOU tariffs

- Treatment 1:

Please read the following text carefully:

There is currently a lot of discussion in Germany about the future of electricity supply. Among other things, electricity consumption is to be reduced at times of day when it is particularly high; for example, in the morning after many people have got up. The high electricity consumption at these times must be compensated by electricity from additional gas and coal-fired power plants. These power plants are otherwise not needed, causing correspondingly high costs and CO<sub>2</sub>-emissions.

For this reason, consideration is being given to adjusting the electricity price during periods of high electricity consumption (i.e., 6 to 10 am and 4 to 8 pm). In these times, the price of electricity would be higher than it is today, otherwise lower. If you were to adjust your electricity consumption accordingly, you could actually pay less overall than you do now.

- Treatment 2:

Please read the following text carefully:

There is currently a lot of discussion in Germany about the future of electricity supply. Among other things, electricity consumption is to be reduced during times when little electricity is available from renewable sources; for example, when wind conditions are poor. If electricity consumption is not reduced during these times, it must be offset by electricity from additional gas and coal-fired power plants. These power plants are otherwise not needed, causing correspondingly high costs and CO<sub>2</sub> emissions. For this reason, consideration is being given to adjusting the price of electricity to the availability of electricity from renewable sources. If the availability is low (you will be informed in time by your electricity provider), the electricity price will be higher than at present, and if the availability is high, it will be lower. If you were to adjust your electricity consumption accordingly, you could pay less overall than you do now.

12. Has your household ever changed its electricity tariff?

- Yes
- No
- Don't know

13. Does your household plan to change its electricity tariff during the next 6 months?

- Yes
- Maybe
- No
- Don't know

14. Who in your household is in charge for decisions in electricity supply (e.g., provider, tariff etc.)?

- Just me

- Me together with others
- Others but me
- Don't know

15. [Only treatment 1]

How often do you use electricity during 6 to 10am and 4 to 8pm?

- Rarely
- Sometimes
- Often
- Very often
- Don't know

16. To what extent do you agree with the following statements? (Options: I fully agree; I rather agree; I rather disagree; I fully disagree)

- Climate change is a serious problem
- My personal actions influence climate change
- Humans are responsible for climate change
- There will be a solution to climate change without limiting our lifestyle
- Scientific predictions regarding climate change are trustworthy
- I am sure that climate change is happening
- Media exaggerates climate change

17. Private households face different options to save electricity. To what extent do you think following options are feasible to decrease electricity consumption? (Options: unfeasible; rather unfeasible; rather feasible; feasible)

- Purchasing an electricity tariff, which electricity price is very high while electricity consumption is high / energy supply from renewables is low and very low otherwise
- Switching off electrical appliances instead of using stand-by
- Increasing average electricity prices
- Switching off lights when leaving a room
- Buying electrical appliances with low electricity consumption
- Replacing old light bulbs or halogen bulbs by electricity saving alternatives
- Other, namely:



18. To what extent do you agree with following statements about an electricity tariff with higher electricity prices while electricity consumption is high/energy supply from renewables is low and very low otherwise? (Options: I fully agree; I rather agree; I rather disagree; I disagree)  
Such an electricity tariff...

- ...ensures that power outages will continue to be rare in Germany
- ...mitigates CO<sub>2</sub>-emissions
- ...increases monthly electricity costs
- ...increases electricity providers' profits
- ...will lead to electricity shortages during certain times
- ...decreases electricity consumption

19. To what extent do you agree with following statements about an electricity tariff with higher electricity prices while electricity consumption is high/energy supply from renewables is low and very low otherwise? (Options: I fully agree; I rather agree; I rather disagree; I disagree)

- I would like to choose such an electricity tariff rather than my current electricity tariff.
- I am doing enough already to save energy; thus, I do not additionally need to choose such an electricity tariff
- My social environment would like it if I would choose such an electricity tariff
- I expect other people around me to behave in an environmentally friendly way
- For me, it would be easy to limit my electricity consumption in case I am at home during 6 to 10am and 4 to 8pm/if there is little electricity from renewables is available.
- Purchasing such an electricity tariff gives me a warm glow to contribute to climate protection
- I do not want others to suffer from the impacts of climate change

20. How willing are you to take risks? (10 Options from 1 “absolutely not willing to take risks” to 10 “absolutely willing to take risks”)

21. How many people belong to your household (including yourself)?

22. How much is your personal monthly net income, today?

Please name your monthly net income, i.e., excluding taxes and social insurance. Please, add regular payments such as pensions, housing allowances, child benefits, BAföG (student benefit), alimony etc.

- Below 1000 €
- 1000 € to under 2000 €
- 2000 € to under 2500 €

- 3000 € to under 3500 €
- 3500 € to under 4000 €
- 4000 € to under 5000 €
- 5000 € to under 7500 €
- 7500 € to under 10,000 €
- 10,000 € or more
- Prefer not to answer

23. How much is your household's monthly net income, today?

Please name your household's monthly net income, i.e., excluding taxes and social insurance. Please, add regular payments such as pensions, housing allowances, child benefits, BAföG (student benefit), alimony etc.

- Below 1000 €
- 1000 € to under 2000 €
- 2000 € to under 2500 €
- 3000 € to under 3500 €
- 3500 € to under 4000 €
- 4000 € to under 5000 €
- 5000 € to under 7500 €
- 7500 € to under 10,000 €
- 10,000 € or more
- Prefer not to answer

24. What is your highest school degree?

- Still in school
- Volks-/Hauptschulabschluss or comparable degree after eight/ninth grade
- Realschulabschluss/Qualified Hauptschulabschluss or comparable degree after tenth grade
- Fachhochschulreife/fachgebundene Hochschulreife/Fachabitur (i.e., graduation after 12th grade allowing access to Fachhochschulen (Universities of applied science))
- General Hochschulreife/Abitur or comparable degree that allows unlimited access to universities

- No degree
- Prefer not to answer

25. What is your current occupation?

- Full-time job (min. 35 h/week)
- Part-time job (15 to 35 h/week)
- Free-lancer
- Housewife/man/child care
- Retired
- Currently unemployed/retraining
- Student/in education
- Prefer not to answer

26. Do you think that individual people may influence future decisions on electricity supply by participating in scientific studies?

- Not at all
- Rather not
- Rather yes
- In any case

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## **Erklärungen**

### **Erklärung zum selbständigen Verfassen der Arbeit:**

Ich erkläre hiermit, dass ich meine Doktorarbeit „Essays on Energy Economics and Consumer Preferences“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautorin maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autor:innen wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autor:innen eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Ort, Datum:

Kiel,

Swantje Sundt