Highlights

The limited potential of regional electricity marketing – Results from two discrete choice experiments in Germany

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Highlight 1: Willingness to pay (WTP) for regional electricity is estimated for two samples.

Highlight 2: WTP for regional electricity is positive but lower than for green electricity.

Highlight 3: Preference heterogeneity can be partly explained by sociodemographic characteristics.

Highlight 4: Regional electricity customers are a subgroup of green electricity customers.

Highlight 5: Regional green tariffs lead to product cannibalization of regular green tariffs.

The limited potential of regional electricity marketing – Results from two discrete choice experiments in Germany

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ABSTRACT

The German energy transition has led to a strong expansion of renewable energies in recent years. As a result, the German population is increasingly coming into contact with generation facilities. To increase local acceptance for new installations and to create new sales channels for energy suppliers, the legislature has established the “System for Guarantees of Regional Origin” in 2019, which allows the marketing of electricity from subsidized facilities as “electricity generated in the region”. However, regional electricity comes with additional costs on the procurement and sales side of energy suppliers, and it is unclear whether and to what extent consumers are willing to pay a premium for electricity generated regionally. This study investigates the willingness to pay (WTP) of residential customers based on two samples of 838 and 59 respondents, respectively. Our model results show that, on average, WTP for regional electricity generation is positive, especially among female, younger and better-educated customers, although differences in WTP between these sociodemographic characteristics are small. Factors that are more relevant are the current type of electricity tariff, differentiated into non-green and green, with the latter having a positive influence, but also the tariff switching behavior of the past, which is a proxy for price sensitivity. Although WTP is positive, it is severely limited, and only pertains to a subgroup of electricity customers. Hence, it is not surprising that our simulation shows that including a regional green electricity tariff in an energy supplier's portfolio is likely to lead to product cannibalization, meaning that mainly green electricity customers will choose this tariff. From an energy supplier's perspective, these results raise the question of whether offering a regional electricity tariff is economically viable. Future research could further investigate what underlying factors drive preferences for regionally generated electricity and how it can contribute to local acceptance.

Keywords:
Choice modeling
Consumer preferences
Willingness to pay
Renewable energies
Electricity tariff
Regional electricity

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1 Introduction

The increase in greenhouse gas concentration over the last decades (IPCC 2020) and the resulting global warming have caused many countries to decide to fundamentally change their energy supply. For example, the German government introduced the Renewable Energy Sources Act (German: Erneuerbare Energien Gesetz, “EEG”) in the year 2000. Its target is a quick transition from conventional power generation based on fossil fuels and nuclear power to the use of renewable energy sources, while keeping energy prices at an affordable level (BMU 2020). Since then, the expansion of renewable energies in Germany has made steady progress. In 2019, renewable energies already covered 42 percent of Germany’s annual gross electricity consumption, corresponding to an increase of 35.7 percentage points since 2000 (UBA 2020). As a result of the expansion, the population is increasingly coming into contact with renewable energies, as e.g., decentralized plants like wind turbines are often located closer to residential areas and thus become visible. Moreover, protests against new generation plants are increasing, especially against wind turbines (see, e.g., Liebe and Dobers 2019).

In order to increase the acceptance for new installations and in response to demands from the energy industry to open up new sales channels for subsidized renewable electricity (Buchmüller 2016; Hölder and Braig 2016), the German legislative established the "System for Guarantees of Regional Origin" (SGRO) in January 2019 (German Environment Agency 2019). The SGRO allows energy suppliers to purchase electricity from subsidized renewable generation plants and to market it as regional electricity to end customers. This requires energy suppliers to obtain both the electricity and the proof of regional generation from a plant operator, called “Guarantee of Regional Origin” (GRO). Hence, the SGRO differs from the “System for Guarantees of Origin” (SGO) defined in article 15 of the European Directive 2009/28/EC (European Union 6/5/2009), which can only be used to prove that a certain share or certain amount of electricity was generated from renewable energies, but cannot be used to guarantee regionality of generation.

To use GROs as proof for regional electricity generation, an energy supplier must fulfill two main requirements: (i) The generation plants must be located within a 50-kilometer radius of the end customer’s community and (ii) a contractual, traceable supply relationship between the respective plant operator(s) and the energy supplier must exist. At the end of the year, the share of regional generation, defined as the ratio between the amount of electricity generated in the region and the amount of electricity consumed in total, can be reported to end customers in the end of year settlement. In addition, with the SGRO, it is legally permitted to advertise regionality of generation (for a brief discussion on the legal aspects of the SGRO see, e.g., Lehmann et al. 2020). However, from a supplier’s perspective, regional electricity is associated with additional costs. These costs arise, for example, from the purchase of regional electricity via over-the-counter (OTC) trading (see Dick and Praktiknjo 2019), by the use of the SGRO (see German Federal Parliament 2018) or by region-specific marketing (see Lehmann et al. 2021). This raises the question of whether it is economically attractive for energy suppliers to market regional generation, i.e., whether customers are sufficiently willing to pay to cover these additional costs. Whereas prior research has primarily examined customers’ willingness to pay (WTP) for renewable electricity, research on regional electricity has largely been lacking. Previous findings on consumers’ WTP for regional electricity are limited and provide no clear insight into the market potential of regional tariffs. This requires more research on customers’ WTP but also raises the question if WTP is heterogeneous across customer segments. Specifically, a marginal (also termed additional) WTP could exist only for subgroups of customers, and it is thus important to identify the factors distinguishing these subgroups. To our knowledge, our research is the first to address this important gap in two ways.

This study aims (i) to determine the marginal WTP (further denoted as WTP) of German household customers for regional electricity under the current regulatory framework, (ii) to compare it with the WTP for other product attributes of electricity tariffs, and (iii) to identify clusters and characteristics of customers, such as sociodemographics and past behavior, which have an influence on WTP. For this purpose, two surveys were conducted at the end of 2019: A survey with a representative sample of 838 German respondents and a specific sample of 59 (potential) customers of the energy supplier *Energiedienst* operating in southern Germany. To determine the WTP, we conducted a choice experiment in which respondents were asked to choose between electricity tariffs in a hypothetical scenario, resulting in two datasets with 10,056 and 708 choices, respectively. Data analysis is performed with a mixed logit model (MIXL) in WTP space using Hierarchical Bayes (HB) estimation and a sophisticated covariate structure. The findings of this paper contribute to the understanding on the importance of regionality in electricity consumption and provide valuable insights for energy suppliers and policymakers.

The paper is structured as follows. In the subsequent Sections 2 and 3, the related literature is presented and hypotheses are derived. The methodology is explained in Section 4 followed by the results in Section 5. Finally, Section 6 concludes with a discussion.

2 Related work

A comprehensive body of research has investigated households' WTP for renewable energies in different countries (for an overview, see, e.g., Soon and Ahmad (2015), Sundt and Rehdanz (2015), Ma et al. (2015), Oerlemans et al. (2016), or Bigerna and Polinori (2019)). These studies indicate that WTP can differ significantly between countries, e.g., due to different levels of awareness or knowledge, attitudes, social norms or socioeconomic characteristics. In addition, many of these studies focus on WTP for the expansion of renewable energies rather than on WTP for an electricity tariff, with the latter being a private good, albeit with externalities (Friege and Herbes 2017). Hence, to ensure comparability to our research context, we focus on studies from Germany on WTP for different attributes of electricity tariffs. These attributes include, inter alia, the *electricity mix,* the *type of energy supplier*, but also the *share of regional generation*.

Electricity mix: The continuous increase in green electricity sales in recent years (see, e.g., VuMA 2020; Hauser et al. 2019, p. 91) indicates that, from an customer's view, the electricity mix is an important attribute of electricity tariffs. Mattes (2012) uses a choice experiment among a representative sample of 1,114 German survey participants and finds that there is a positive WTP of 2.19 cents per kWh for electricity exclusively from renewable sources. Sauthoff et al. (2017) come to comparable results and estimate a WTP of 2.4 cents per kWh for a share of 100% renewables in the electricity mix. They also note differences between generation technologies, with solar and wind energy being preferred over biogas and a generic renewable electricity mix. A pure solar and hydropower electricity mix is also preferred by customers over a generic green electricity mix in the study by Kalkbrenner et al. (2017), but only with a small difference of 0.85 euros per month. In contrast, Kaenzig et al. (2013) do not find an additional WTP for wind energy compared to a generic green electricity mix. Yet, they confirm an additional WTP of around 12 euros per month for carbon-free electricity, i.e. from nuclear and renewable energies compared to electricity from coal-fired generation. In a more recent choice experiment among 274 respondents, Bengart and Vogt (2021) show that the way the electricity mix is presented, i.e., a breakdown of the energy sources vs. an aggregated view, can influence customers' WTP both, positively and negatively, depending on energy source. Sagebiel et al. (2014) also use a choice experiment to estimate the WTP for different shares of renewable energies in the electricity mix. While a model estimating the mean WTP of all respondents confirms the results of previous studies with a positive WTP for renewables (of 22.26 euros and month), estimating the WTP for (latent) classes of respondents shows strong differences between them, with one class having a WTP only marginally above zero. Investigating the question of whether it is sufficient that an electricity tariff is carbon-free or whether generation technologies also matter, Grösche and Schröder (2011) use a representative sample of 2,948 respondents from 2008 to show that there is a positive WTP of 22.23% for 100% renewable energies and a negative WTP for 100% nuclear energy of -20.10%, indicating that consumers prefer other generation technologies over nuclear. Kaenzig et al. (2013) confirm this negative attitude of the population towards nuclear energy (see, e.g., Arlt and Wolling 2016; Wang and Kim 2018), resulting in a positive WTP of 6.50 euros per month for the German default electricity mix, but without nuclear energy. Beyond these studies, little research has examined variations in WTP for different types of renewable energy installations in the context of electricity tariffs in Germany.

Type of electricity supplier: Though no general classification exists, energy suppliers can be distinguished by criteria such as the size of the customer base or supply area, company location, ownership structures or corporate objectives. Moreover, electricity suppliers may vary in their reputation, image, trust by customers, and regional ties, which could influence the evaluation of electricity tariffs by end customers. For Germany, Burkhalter et al. (2009), Günther et al. (2019) and Fait et al. (2020) find that customers have a higher WTP for energy suppliers with regional ties. They show that German electricity customers prefer local electricity suppliers to geographically more distant or larger electricity suppliers. In contrast, the survey participants of Kalkbrenner et al. (2017) prefer a regional to a local electricity supplier, resulting in an additional WTP of 2.26 euros per month and household, which could be an indicator for a positive association with the term regionality. In addition to familiarity and regional ties, ownership structures can also play a role when different suppliers are evaluated by electricity customers. In the study by Rommel et al. (2016), community owned energy suppliers (compared to investor-owned suppliers) are most preferred, with an additional WTP of 1.82 cents per kWh. Cooperative energy suppliers are less preferred with 0.55 cents per kWh. Sagebiel et al. (2014) use a choice experiment to delve deeper into the characteristics of electricity suppliers, e.g., in terms of transparency, participation, democratic decision-making, company location and the number of shareholders. Their results reveal that these characteristics have a positive influence on the possibility of respondents choosing an electricity tariff. Another study by Mattes (2012) shows that the investment behavior of a company in renewable energies is also relevant for electricity customers.

Share of regional generation: The trend toward regional products known from other sectors is increasingly spilling over into the energy sector (Lehnert and Rühr 2019). So far, only a few studies have dealt with the WTP for regional electricity generation from the perspective of household customers. Kaenzig et al. (2013) analyzed their representative sample of 414 German household customers from 2009 to see how WTP for regional electricity differs from the WTP for domestic or foreign electricity. They find no additional WTP for electricity from the region, but a negative WTP of around minus 3 euros per month for electricity from Switzerland and of around minus 5 euros for electricity from Eastern Europe. In their 2014 survey, Kalkbrenner et al. (2017) find a positive WTP of 0.71 euros per month for a 33% share of regional generation. However, the 953 German respondents do not show any WTP for higher shares of regional generation. In a more recent study by Günther et al. (2019), 663 respondents were asked about their preferences for electricity from a regional wind farm. The results of this study show that the WTP increases by up to an average of 17 euros per month if 100% of the electricity comes from this wind farm. This WTP increases further if regional priming or environmental priming are used (Fait et al. 2020). By contrast, Bengart and Vogt (2021) find a substantially lower WTP of 1.67 euros per month for regional electricity. However, unlike Günther et al. (2019), they do not provide information to their respondents on which areas the region includes.[1]

To summarize, whereas research has examined the relevance of the electricity price, the electricity mix, and (to a lesser extent) the type of supplier, little research has examined the WTP for regionality of generation. Notably, the few studies examining the WTP for regional electricity do not show consistent findings. This suggests that the WTP for regional electricity might differ between subgroups of customers, but findings on the underlying factors and their correlations are missing. For example, none of the studies conducted so far used respondents' sociodemographic characteristic to explain preference heterogeneity, nor did any of them conduct research on customer segments (for an overview on the cited studies from Germany and their methodologies used, see Table 8 in the Appendix). More research is necessary that disentangles different confounding aspects of regional generation and allows better insights into the potential of regional electricity.

3 Hypotheses

Prior to this research and in addition to the literature review, we conducted 17 expert interviews on regional electricity tariffs with representatives of different energy suppliers in Germany (Lehmann et al. 2021). The experts were representatives of the business segments sales, procurement and management. The interviews gave insights into the end customer business, the procurement of regional electricity and the long-term strategic orientation of energy suppliers, and thus helped in deriving hypotheses for this study.

From an end customer perspective, regionality in electricity generation may be positive, negative or neither (Kreuzburg 2018), depending on whether "not in my back yard" (NIMBY) effects are of concern or not (see, e.g., Kalkbrenner et al. 2017; Tabi et al. 2014; Vecchiato and Tempesta 2015). However, if the SGRO and its definition of regionality as a 50 km radius are used, NIMBY effects are likely to play a subordinate role, as generation facilities may not even be in sight from end customers' homes. Accordingly, and given the trends toward regionality in other sectors, our first hypothesis is as follows:

H1: *The higher the share of regional generation in electricity tariffs, the greater the WTP.*

From an energy supplier's perspective, it is essential to know which customers prefer regional generation. Preference heterogeneity may, at least to some extent, be explained by sociodemographic characteristic. Literature from the field of preferences for green electricity indicates that gender (e.g., Andor et al. 2020), age (e.g., Sauthoff et al. 2017), and education (e.g., Tabi et al. 2014) have an impact on WTP, allowing for the assumption that these effects may also hold for regional generation. Furthermore, the trend towards regionality in other sectors is particularly prevalent in urban areas (e.g., Hempel and Hamm 2016), which may be true for regional electricity generation as well. Since the experts pointed in the same direction in the interviews, we hypothesize the following:

H2: *Female, younger or better educated electricity customers are more willing to pay for green and regional electricity. The same holds for electricity customers in urban areas.*

In addition, we expect that there are some characteristics of electricity customers that affect their price sensitivity in general, defined as a response to a relative price change, and not only the price sensitivity for specific attributes of an electricity tariff. These characteristics include the household net income, but also the monthly expenditures on electricity. The latter is based on the assumption that relative price markups are more likely to be accepted if the absolute monthly advance payment is low, and vice versa. These considerations lead to the next hypothesis:

H3: *The higher the monthly advance payment, the more price sensitive the end customer. The opposite correlation holds for the net household income.*

While sociodemographic characteristics are usually told to have limited explanatory power for purchasing decisions (see, e.g., Hess 2014; Kurz and Binner 2011), current or past behavior may be stronger predictors of electricity customers' preferences. According to the experts, on the one hand this behavior includes the choice of the current electricity tariff (green vs. conventional tariffs), but

[1] In addition to the attributes outlined so far, eco-labels (e.g., Kaenzig et al. 2013; Mattes 2012; Lehmann and Beikirch 2020), price guarantees (e.g., Kaenzig et al. 2013; Mattes 2012; Sauthoff et al. 2017; Bengart and Vogt 2021), or switching bonuses (e.g., Sauthoff et al. 2017) may be other product attributes of electricity tariffs, but seem to be less important.

also whether consumers switched their tariffs in the recent past (see also Sauthoff et al. 2017; He and Reiner 2017). Hence, we derive the next two hypotheses:

> ***H4:*** *Electricity customers who already purchase green electricity show a higher WTP for renewables electricity mixes, but also for regional electricity.*

> ***H5:*** *Electricity customers who changed their electricity tariff or electricity supplier in the past are more price sensitive.*

Preferences may also vary with regard to types of energy suppliers, which differ, for example, in terms of company size, image or regional ties. In addition, little is known about how energy suppliers' customer bases differ in preferences for regional electricity. In the interviews, some experts pointed out that the customer bases of municipal and citizen energy suppliers may be more open to new, sustainable and regional products. Drawing upon these statements, we assume that these customers have an additional WTP for regional generation.

> ***H6:*** *Customers of municipal energy suppliers and citizen energy suppliers have a higher WTP for regional generation than customers of national energy suppliers.*

Although WTP can – at least to some extent – be explained by sociodemographic characteristics and past behavior, it is still largely uncertain how the introduction of new regional electricity tariffs affects sales of existing electricity tariffs. Related work and current market developments (Hauser et al. 2019, p. 91) have shown that parts of the German population are willing to pay a price premium for green electricity. These preferences may partly be driven by environmental concerns (see, e.g., Bamberg 2003; Kalkbrenner et al. 2017). At the same time, research in the field of foods has shown that the same environmental concerns push preferences for regional products (e.g., Hempel and Hamm 2016; Meyerding et al. 2019). Building upon these findings, preferences for green electricity may spill over to regional electricity. In the interviews, experts also suggested customers who prefer regional electricity to be the same customers who prefer green electricity, leading to a risk of product cannibalization. Hence, we conclude with the last hypothesis:

> ***H7:*** *Regional electricity customers are a subgroup of green electricity customers.*

4 Methodology

4.1 Experimental and survey design

To answer the key research question of whether it is economically attractive for energy suppliers to market regional electricity that entails additional costs on the procurement and sales side, values for the WTP of household customers must be estimated. In the literature, there are various methods for measuring WTP for marketable and non-marketable goods (for a brief comparison, see Breidert et al. 2006). Choice experiments are a method that has been frequently used in recent years (Keane and Wasi 2012; Hensher 2014). In choice experiments, choice situations are simulated and respondents have to pick their preferred alternative in one or more choice situations. Each alternative consists of several attributes, such as the share of regional generation with varying levels. From the observations of the choice situations, preferences and, if a price attribute is included, WTP can be derived. Choice experiments are based on two theories. First, the theory of consumer behavior by Lancaster (1966) postulates that the utility of an alternative results from its attributes. Secondly, according to McFadden's (1974) random utility theory, a person always chooses the alternative that gives him or her the highest utility, although an error term can lead to deviations from optimal choices. One major advantage of choice experiments is the possibility of including non-marketable or hypothetical alternatives (Ryan et al. 2012). However, other preference elicitation methods, such as the contingent valuation method (CVA), offer this possibility as well. Yet, they lack realism. In contrast, choice experiments represent daily life situations forcing people to make trade-offs (Johnson and Orme 1996; Desarbo et al. 1995). In addition, respondents tend to be less likely to give strategic answers (Sauthoff et al. 2017; Mariel et al. 2021, p. 27) or socially desirable answers (Donche et al. 2015, p. 87). Choice experiments are particularly suitable for low-involvement decisions such as electricity tariffs (see Huber et al. 1992), as respondents generally attach little cognitive effort to such purchase situations (see Dütschke and Paetz 2013; Layer et al. 2017), thus leading to more realistic responses.

We defined four relevant attributes of electricity tariffs: (i) the *type of supplier*, (ii) the *electricity mix*, (iii) the *share of regional generation* and (iv) the *price (markup)*. For the first attribute, current market observations allow for a rough division into three types: *National energy suppliers*, *municipal energy suppliers* and *citizen energy suppliers*. *National suppliers* (reference level) are characterized by a large customer base covering all or substantial parts of Germany. *Municipal energy suppliers*, on the other hand, can be found all over Germany and have supply areas which are geographically limited. Furthermore, these suppliers are often characterized by regional ties, e.g., through co-ownership or company history. The third type comprises *citizen energy suppliers*, a civic form of cooperative participation (Yildiz 2014).

For the *electricity mix*, we defined four attribute levels: A *default mix*, a *renewables mix*, a *wind mix* and a *solar mix*. The default mix (reference level) is based on the relative shares of Germany's gross electricity generation from 2018 (AGEB 2019), but without nuclear energy, as Germany will phase out nuclear energy by 2022 (see BMWi 2016). For the *renewables mix*, the relative shares of conventional energy sources are subtracted. Both a *wind* and a *solar mix* were included to account for preference heterogeneity, as wind and solar are among the dominant energy sources for renewable electricity generation in Germany today (see UBA 2020). It is important to note that the electricity mix in the end-of-year settlement is determined using energy quantities over a period of one year, i.e., there is no real-time supply with the electricity mix.

Current regulation limits the *share of regional generation* that can be reported in the year-end statement, given a customer purchases regional electricity, to the share of subsidized generation (see paragraph 79a (8) EEG). At the time of the survey, this maximum share possible was 52.94% (netztransparenz.de 2018). However, it is difficult to convey this limitation to end customers (Lehmann et al. 2021). For ease of communication, we set the levels for the *share of regional generation* at *0%* (reference level), *50%* (roughly reflecting the maximum share the current regulatory framework allows), and *100%*.

The monthly and yearly electricity *prices* displayed were calculated individually for each respondent based on their current advance payment for electricity. This offers two advantages: First, using individual prices reflects differences in utility more realistically than using fixed prices (Killi et al. 2007; Gensler et al. 2012). Secondly, it is less cognitively demanding than markups in percentages or prices in cents per kilowatt-hour (see Layer et al. 2017), resulting in an increased choice consistency (see Hensher et al. 2005b) and in a reduced use of heuristics (see Leong and Hensher 2012). For respondents not aware of those costs, the value was approximated based on the household size, with prices from CHECK24 (2020) and electricity consumption from Verivox (2019), Germany’s two largest price comparison websites for electricity tariffs. With these prices as individual base prices (*0%* markup), the other price levels were calculated by adding a markup of *5%*, *10%* and *15%*. Although there are green electricity tariffs available on the market for lower markups (see Hauser et al. 2019, p. 92), these levels are still realistic. Moreover, some inflation of the price attribute is necessary to force respondents to make trade-offs in a hypothetical choice situation (Ryan et al. 2012; Holmes et al. 2017). Table 1 summarizes the attributes and levels used in the choice experiment.

Table 1: Attributes and levels in the CBC design.

Attributes	Levels			
Type of supplier	National energy supplier[a]	Municipal energy supplier	Citizen energy supplier	
Electricity mix	Default mix[a,b] 31% coal 11% natural gas 5% other 27% wind energy 11% biomass 11% solar power 4% hydropower	Renewables mix[b] 51% wind energy 21% biomass 21% solar power 7% hydropower	Wind mix[b] 100% wind energy	Solar mix[b] 100% solar power
Share of regional generation	0%[a]	50%	100%	
Price markup	0%[a,c]	5%[c]	10%[c]	15%[c]

[a] Reference level.
[b] Names not shown in the CBC tasks.
[c] Displayed as monthly and annual prices based on the current advance payment for electricity or approximated by household size.

We conducted two identical online surveys in Germany in late 2019. The first part of the two surveys explained the attributes and levels of electricity tariffs and asked respondents about their awareness regarding these attributes, measured using four response options. A choice experiment followed in the second part, where respondents had to choose 15 times between three electricity tariffs. Previous studies have shown that with 15 choice sets, the advantages of more observations per respondent outweigh the disadvantages of potentially bored or exhausted respondents (e.g., Ryan et al. 2012; Johnson and Orme 1996; Hensher et al. 2001). Of these 15 choice sets, one was an introductory choice set (see Mariel et al. 2021, pp. 23–24) and two were holdout choice sets to investigate external validity (see Orme 2015). In addition, we refrained from including a none-option to force respondents to make trade-offs (Allenby et al. 2013; Ryan et al. 2012).

The D-optimal statistical design (see Rose and Bliemer 2014) was created using the software R (R Core Team 2019) and the package 'choiceDes' by Horne (2018). For sufficient variation in the choices without affecting respondent efficiency and to avoid sequencing effects, we used a blocked design (see Reed Johnson et al. 2013). The design was divided into 300 blocks (Sawtooth Software Inc. 2021b) using the blocking algorithm by Cook and Nachtsheim (1989). The third and fourth part of the survey comprised attitudinal questions and questions about respondents' expectations regarding regional electricity. The survey concluded with questions about sociodemographic characteristics of the respondents.

To reduce the risk of hypothetical bias, we reminded respondents of their budget constraint in every choice set by displaying their current monthly advance payment for electricity (see also Mozumder et al. 2011; Arrow et al. 1993). In addition, to enhance the realism of the choice sets, graphics were used for the attribute levels and info buttons were included with information about the attributes and levels. An exemplary choice set is shown in Figure 4 in the Appendix. However, there is still a risk of low data quality, especially in online surveys (see Smith et al. 2016). One source of error is speeding, defined as answering so quickly that respondents could not have given much, if any, thought to their answers (Conrad et al. 2017). Instead of measuring response times after the survey, we followed Zhang and Conrad (2014) and Conrad et al. (2017) and included immediate pop-up prompts for respondents answering faster than the time required for silent reading. For the choice part, we used the median time required for one task from the pretest, albeit reduced by 30% (see Greszki et al. 2014).

4.2 Statistical models

To estimate WTP for the different attribute levels, we used random parameter mixed logit (MIXL) models (see Hensher and Greene 2003), as the basic multinomial logistic (MNL) model introduced by McFadden (1974) does not allow to incorporate unobservable heterogeneity. MIXL models are one of the most common models used in choice modeling today (Sarrias and Daziano 2017; Keane and Wasi 2012). They give the analyst flexibility in model specification and thus great potential to gain insights into the choice behavior of respondents (Hensher and Greene 2003), especially compared to the MNL model (see, e.g., Hensher and Greene 2011a; Hensher and Greene 2003). However, this flexibility comes at a cost, i.e., the analyst must specify parameter distributions and correlation structures. Furthermore, MIXL models pose high demands on data quality (Hensher and Greene 2003) and quantity (Hess and Train 2011). In our case, however, there are sufficient observations, both at the sample and respondent level.

For the estimation of the MIXL models, we used Hierarchical Bayes estimation (see Howell 2009), which allows to combine information at an aggregated level to be combined with observations at the level of the respondents and thus to derive individual parameter estimates (Orme 2000). This offers advantages over estimating multiple models separately, e.g., in terms of data quantity (see Rossi et al. 2009, p. 3; Kurz and Binner 2011). Compared to Maximum Simulated Likelihood, HB has computational advantages (see, e.g., Train 2001; Huber and Train 2001) and is less prone to the misspecification of starting values (Regier et al. 2009).

HB models consist of two levels. At the upper level, it is assumed that the vector of a respondent's part-worth utilities β_n, separated into non-price part-worth utilities $\beta_n^{Attributes}$ and the (negative) part-worth utility for the price attribute β_n^{Price}, originates from a population whose preferences can be expressed with a multivariate distribution. The lower model assumes that respondents make their choices according to the MNL method, i.e. respondent n chooses alternative j in choice situation t, which gives him or her the highest utility U (Howell 2009; Orme and Howell 2009), where X denotes the design matrix and ε the error term. To account for left-right effects, we further integrated alternative-specific constants c_j (see Daly et al. 2016), so utility is given by:

$$U_{n,j,t} = c_j + \beta_n^{Attributes\prime} X_{n,j,t}^{Attributes} + \beta_n^{Price} X_{n,j,t}^{Price} + \varepsilon_{n,j,t} \tag{1}$$

As WTP $\omega_n^{Attributes}$ is denoted as the negative ratio between the part-worth utilities of the non-price attributes $\beta_n^{Attributes}$ and the price coefficient β_n^{Price}, i.e. $\omega_n^{Attributes} = -(\beta_n^{Attributes}/\beta_n^{Price})$, equation (1) can be rewritten as:

$$U_{n,j,t} = c_j - (\beta_n^{Price} \omega_n^{Attributes})' X_{n,j,t}^{Attributes} + \beta_n^{Price} X_{n,j,t}^{Price} + \varepsilon_{n,j,t} \tag{2}$$

which leads to the MIXL model in WTP space (Train and Weeks 2005). Empirical evidence suggests that models in WTP space lead to more realistic WTP estimates than models in preference space (e.g., Scarpa et al. 2008; Hole and Kolstad 2012; Train and Weeks 2005; Hensher and Greene 2011b).We assumed that WTP for each attribute level is normally distributed, i.e. $\omega^{Attributes} \sim N(\mu^{Attributes}, \sigma^{2Attributes})$, while the price coefficient was assumed to be linear with a negative lognormal distribution, i.e. $\beta^{Price} \sim -LN(\mu^{Price}, \sigma^{2Price})$. The latter is necessary to restrict the price coefficient to negative values.[1]

To check if sociodemographics or past behavior have an influence on WTP, covariates $\delta^{Attributes}$ were integrated into the models (see Crabbe and Vandebroek 2012). Covariates were modelled as fixed coefficients and entered either as mean-centered continuous or dummy variables z_n (see Orme and Howell 2009). Gender, age, education, community size and the federal state, differentiated

[1] Note that a lognormal random variable is just a transformation of a normal random variable, i.e. the WTP coefficients and the logarithm of the price coefficient are multivariate normally distributed, which is computationally advantageous given its conjugation property (for details on distributional assumptions in HB, see, for example, Rossi et al. 2009, p. 20; Train 2001; Bouriga and Féron 2013).

into federal states with high shares of solar and wind capacity, were integrated as sociodemographic covariates of the WTP coefficients. We used a log transformation for education to account for a decreasing marginal influence on WTP. The current electricity mix, differentiated into green and non-green, and the current type of supplier are covariates for past behavior. For the WTP coefficients, covariates entered the model additively, i.e. $\tilde{\omega}_n^{Attributes} = \omega_n^{Attributes} + \delta^{Attributes} z_n$. By contrast, covariates of the price coefficient δ^{Price} entered the model multiplicatively, i.e. $\tilde{\beta}_n^{Price} = \beta_n^{Price} \cdot \delta^{Price} z_n$. Covariates of the price coefficient are the net household income z_n^{Income}, the current advance payment for electricity $z_n^{PriceMonthly}$, and a dummy $z_n^{Switched}$ of whether a respondent switched the electricity tariff or supplier within the last three years. Note that the covariates of the price coefficient enter only the third term of equation (2) to avoid multiplication by the scale parameter (see Hess and Train 2017). Following Hess et al. (2018), we directly estimated the income elasticity λ^{Income} and price elasticity $\lambda^{PriceMonthly}$. However, not all respondents stated their income, which was accounted for by a dummy variable $z_n^{IncomeMiss}$. This results in the final price coefficient:

$$\tilde{\beta}_n^{Price} = \beta_n^{Price} \cdot \left(z_n^{IncomeMiss} \cdot (1 + \delta^{IncomeMiss}) + (1 - z_n^{IncomeMiss}) \left(\frac{z_n^{Income}}{\overline{z_n^{Income}}} \right)^{\lambda^{Income}} \right) \cdot \left(\frac{z_n^{PriceMonthly}}{\overline{z_n^{PriceMonthly}}} \right)^{\lambda^{PriceMonthly}} \cdot (1 + \delta^{Switched} z_n^{Switched}) \tag{3}$$

Prior to integrating covariates into the model, we checked for bivariate correlations (see Orme and Howell 2009). The highest correlation found was -0.42, indicating no strong multicollinearity (see Dormann et al. 2013). As covariates increase the number of parameters to be estimated, this can lead to problems with small samples (see, e.g., Mariel et al. 2021, p. 118; Bekker-Grob et al. 2015). We therefore controlled only for the effects of covariates on selected, but not all WTP coefficients. In addition, for the second and smaller *Energiedienst* sample, the covariates were limited to sociodemographics and their influence on the *share of regional generation* and the *price*, leading to a more parsimonious model. An overview of the covariates and their coding can be found in the Appendix in Table 11 and Table 12.

For model estimation, we relied on the R package 'Apollo' (Hess and Palma 2021) and its implementation of HB by Keller et al. (2017). Dummy coding was used for the attribute levels for ease of interpretation (see Daly et al. 2016). Tests of significances are based on Bayesian credible intervals (Hall and Hall 2020), a part of Bayesian inference (see Lenk 2014). Further information on parameters used in model estimation can be found in the supplementary material.

To test internal and external validity, we calculated the HIT rate, both for the twelve choice tasks used for model estimation and for the two holdout tasks. The HIT rate measures the percentage of correct predictions in a given data set (Louviere et al. 2000b, p. 56). The internal (external) HIT rates of the panel and *Energiedienst* sample are 86.3% (69.5%) and 89.7% (67.8%), respectively. Compared to the naive model with a HIT rate of 33.33%, these results indicate a good model fit.

In order to draw conclusions about customer groups, the conditional WTP estimates of the respondents must be analyzed and classified. For this purpose, methods from the field of cluster analysis can be used. A classification method that has been frequently used in the recent past are Gaussian Mixture models (see Scrucca et al. 2016). These models offer advantages over other clustering methods such as kmeans, e.g., by allowing for soft classification (see Izenman 2008, p. 453). With Gaussian Mixture models, the individual WTP estimates are assigned to the clusters probabilistically. For model estimation, we used the R-package ‘mclust’ (Fraley et al. 2020) and its implementation of the EM-algorithm (Dempster et al. 1977).[1]

4.3 Sample characterizations

Data was collected using an online survey created with *Lighthouse Studio* (Sawtooth Software, Inc. 2020). Two samples of German household customers were collected: A quota sample of 941 respondents from a professional online panel provider that is representative of Germany in terms of gender, age, education and household size (see gik 2018). A second convenience sample comprises 60 (potential) customers of the German energy supplier *Energiedienst*, who were acquired using a pop-up on the *Energiedienst* website. The collection of two samples provides valuable insights into the preferences of the German average

[1] In addition to MNL and MIXL models, there are many other estimation models for data from choice experiments (for an overview and comparison, see e.g., Keane and Wasi 2012). In particular, the latent class mixed logit (LC-MIXL) model (see Greene and Hensher 2013) should be noted which combines the latent class approach (see Greene and Hensher 2003) with another layer of preference heterogeneity within each class. This results in a simultaneous estimation of class membership probability and individual parameters, which is more efficient compared to sequential estimation. However, LC-MIXL models place high demands on data quantity, especially when incorporating covariates. For a discussion on clustering based on conditional estimates, see, for example, Eagle and Magidson (2020).

electricity customer, but also of a specific customer group. All survey participants were at least 18 years old and (co-)responsible for choosing an electricity tariff in their household.

Data was cleaned using four criteria. Specifically, we screened out participants (i) with extreme response behavior in the choice tasks (see Schlereth and Skiera 2017), (ii) with no variance or excessive "don't know" responses in the attitudinal questions (see Schonlau and Toepoel 2015), (iii) with randomized choices in combination with speeding behavior (see Orme 2019), defined as being faster/slower than 95% of the sample, and (iv) with answers of no meaning in free-text fields. This led to the final samples with 838 and 59 respondents, respectively (see Table 2).

Table 2: Sample characterizations.

		Panel sample (N = 838) Frequency [%]	*Energiedienst* sample (N = 59) Frequency [%]	German average[a] Frequency [%]
Gender				
	Male	48.3	81.4	49.5
	Female	51.6	18.6	50.5
Age				
	18-24 years	9.8	5.1	11.9
	25-29 years	12.7	3.4	7.2
	30-39 years	15.7	23.7	14.8
	40-49 years	19.6	13.6	15.0
	50-59 years	23.6	27.1	19.0
	60 years or older	18.6	27.1	32.1
Education				
	No degree	0.6	0.0	4.2
	Secondary school graduate	39.7	10.2	30.8
	General certificate of secondary education	23.3	28.8	31.1
	General higher education qualification	36.4	61.0	33.9
Household size				
	1 person	19.7	11.9	41.9
	2 persons	36.7	39.0	33.8
	3 persons	23.9	25.4	11.9
	4 persons	15.0	15.2	9.0
	5 or more persons	4.7	8.5	3.4

[a] Own calculations based on data for 2018 of the Federal Statistical Office (Federal Statistical Office 2020b, 2020a, 2020c).

The panel sample is still largely representative after data cleaning (see Table 9 in the Appendix), although deviations from the classification of the Federal Statistical Office are apparent: The top age and the lowest education classes are underrepresented, whereas multi-person households are overrepresented. However, these are well-known problems of panel samples. The *Energiedienst* sample also reveals deviations from the national average: The sample is dominated by male, well-educated respondents, aged 30-39 and 50-59, respectively, living in a multi-person household. In the panel (*Energiedienst*) sample, 91.65% (89.83%) reported their net household income, 80.07% (79.66%) were aware of their monthly advance payment, and 34.13% (35.59%) had changed their electricity tariff in the past three years.

5 Results

5.1 Descriptive analysis

One of the main drivers of WTP may be the degree of consistency between what consumers' expectations of electricity tariffs are and what they are offered on the market (see Kaenzig et al. 2013). Therefore, we asked respondents to indicate the degree of consistency between the legislative definition and their expectations of regional electricity. On a seven-point Likert scale, respondents indicated agreement with a mean (median) of 5.232 (5.0) in the panel sample and 4.78 (5.0) in the *Energiedienst* sample. Hence, the legislative definition of regional electricity does not seem to completely miss our respondents' expectations. In fact, another question shows that larger geographical areas, such as districts and federal states, are more likely to meet their expectations than smaller geographical areas, e.g., municipalities or neighborhoods (see Figure 1).

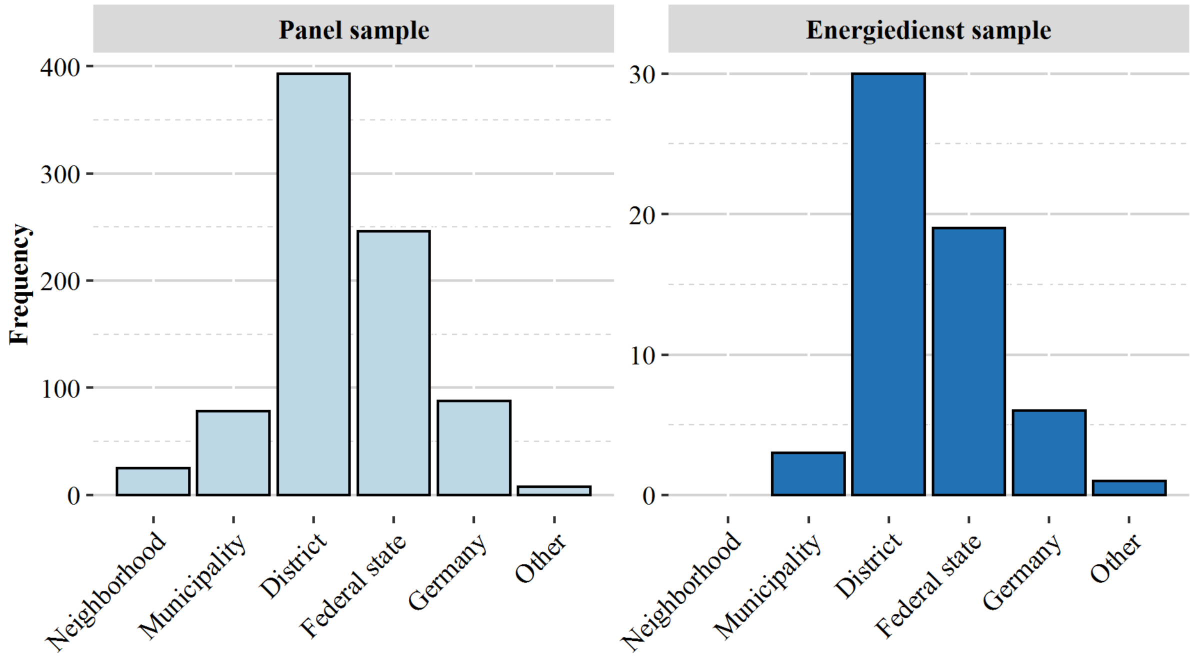

Figure 1: Geographical areas consistent with respondents' expectations of regional electricity for the panel sample (N=838) and the *Energiedienst* sample (N=59).

From an energy supplier's perspective, this is good news, as smaller geographic areas can significantly limit accessibility to generation facilities (Lehmann et al. 2021). Furthermore, this information may be a first indicator that regionality in electricity generation may be an attribute of electricity tariffs consumers are willing to pay for.

5.2 Willingness to pay

5.2.1 Attributes

The results of the MIXL model in WTP space are shown in Table 3. These are the posterior means for the random WTP coefficients $\omega^{Attributes}$ and the price coefficient β^{Price}, i.e., the continuous and dummy-coded covariates are set at their mean and reference levels, respectively. WTP is measured in percentage points. All WTP coefficients, except for the *citizen energy supplier* in the panel sample, have the expected sign, i.e. a change from the reference level leads to an increase in WTP.

Starting with the *type of supplier*, it emerges that respondents do have a positive additional WTP of 1.000% for electricity from *municipal energy suppliers* in the in panel sample and 6.597% in the *Energiedienst* sample, compared to a *national energy supplier* as reference level. WTP is also positive for electricity from *citizen energy suppliers*, but only in the *Energiedienst* sample (5.466%). In the panel sample it is negative (-0.223%) which contradicts the results of previous studies (cf. Sagebiel et al. 2014; Kalkbrenner et al. 2017). This could be for two reasons: First, *citizen energy suppliers* could be attributed with a lack of energy knowledge, leading to a reduced level of trust and thus a lower probability of choosing this *type of supplier* (see also Lehmann et al. 2020). In addition, the sentiment in the German population towards the energy transition is polarized and often reflects immediate responses to emotions (Sütterlin and Siegrist 2017), which may lead to an aversion towards citizens actively supporting this transformation process. It should be kept in mind, however, that this negative WTP is of small magnitude and not significant in the upper level (see Table 10 in the Appendix). In conclusion, from a nationwide perspective, the *type of energy supplier* is considered relatively unimportant, whereas specific customer groups (as shown by the *Energiedienst* sample) place strong emphasis on this attribute.

Marginal WTP is highest for the *electricity mix* from renewables in both samples. All *electricity mixes* show positive values. These estimates are in line with related work (see Section 2). What is surprising, however, is that WTP is highest for the generic *renewables mix* (4.406% and 24.010%) and lowest for the *wind mix* (1.905% and 17.006%), which does not coincide with prior research stating that respondents prefer pure electricity mixes (cf. Sauthoff et al. 2017; Kalkbrenner et al. 2017; Kaenzig et al. 2013). Current market activities also reveal that some energy suppliers have already started to offer electricity tariffs with high shares of solar and wind energy (e.g., BUZZN 2021; Thüringer Landstrom 2021). While the low WTP for the *wind mix* can at least partially be attributed to the public's reluctance to wind turbines (see Sonnberger and Ruddat 2017), the reason for the *solar mix* ranked second, even though being a publicly accepted generation technology (see Liebe and Dobers 2019; Sütterlin and Siegrist 2017), may be security of supply (see Yang et al. 2016). The fact that security of supply is ensured at any time independent of the *electricity mix* appears to be unknown at least to some respondents, as mentioned at the end of the survey in the comments box. Another noteworthy aspect of the *electricity mix* are its high standard deviations, which indicate strong heterogeneity in WTP. Besides these differences and heterogeneity in WTP, additional WTP is much higher in the *Energiedienst* sample, preliminarily supporting the assumption that customers of municipal energy suppliers have a higher WTP for regional generation (H6), which will be further investigated in Section 5.2.2.

When it comes to the *share of regional generation*, differences between the two samples are smaller. Similar to the *electricity mix*, the parameter estimators for a *50%* and *100% share of regional generation* are positive, indicating that, on average, regionality is perceived as a positive product attribute in electricity tariffs. This result supports H1. However, WTP is low in magnitude, ranging from 1.785% in the panel sample to 5.140% in the *Energiedienst* sample. These absolute figures are in line with those of Bengart and Vogt (2021) (1.12 euros per month for electricity from the region) and may be a disillusioning result from an energy supplier's perspective. Still, in the panel sample, the mean WTP for *100% regional generation* even exceeds the WTP for the *wind mix*, meaning that for some respondents *regional generation* is more valuable than wind energy.[1] Compared to the results of Kaenzig et al. (2013) and Kalkbrenner et al. (2017), who found no and marginal additional WTP for *regional generation*, the increase in WTP is substantial, but still small in absolute terms. This may be a result of time, as regionality has only recently gained importance in other sectors as well.

Table 3: Posterior means for the random coefficients (excluding covariates). Additional WTP (in percent) for a change from the reference levels.

		Panel sample		Energiedienst sample	
Attribute	Level	post μ	post σ	post μ	post σ
Type of supplier	National energy supplier	-	-	-	-
	Municipal energy supplier	1.000	1.279	6.597	4.693
	Citizen energy supplier	-0.223	1.160	5.466	4.533
Electricity mix	Default mix	-	-	-	-
	Renewables mix	4.406	6.041	24.010	11.966
	Wind mix	1.905	7.881	17.006	8.429
	Solar mix	3.023	8.160	19.857	9.975
Share of regional generation	0%	-	-	-	-
	50%	1.785	1.078	3.856	1.660
	100%	2.872	2.494	5.140	3.348
Price[a]	[100%;115%]	-1.087	0.842	-2.150	4.197

[a] Continuous attribute in preference space, lognormally distributed.

5.2.2 Covariates analysis

The results on the sociodemographic covariates can be found in Table 4 and Table 5. Since the sample size of the *Energiedienst* sample is small, we focus the interpretation on effect sizes rather than significance levels.[2]

The results show that women have a higher WTP for *regional generation* than men in both samples. This effect is particularly pronounced in the *Energiedienst* sample, with an additional WTP of 5.479% for *100% regional generation.* In the panel sample, this effect is much smaller at 1.002%, and comparable to the effect of gender on the *renewables electricity mix* (1.336%). In contrast to gender, the effect of age on the WTP for *100% regional generation* is negative in both samples, with -0.255% in the panel and -0.442% in the *Energiedienst* sample. However, this effect is only significant on the 10% level in the panel sample and far less pronounced compared to the effect of age on the WTP for the *electricity mixes* (-0.590%, -0.730%, -0.789%). These results are somewhat surprising, as the positive effect of gender on the WTP for renewable energies seems to spill over to *regional generation*, whereas the negative WTP of older respondents for renewable energies does not affect WTP for *regional generation* to the same extent, if at all.

When looking at the influence of education on the WTP estimates for *regional generation*, none of the effects is significant in either sample. The effect sizes, however, indicate that WTP for *regional* generation may be higher among more highly educated persons. Education could also be hypothesized to have a positive effect on WTP for the renewable *electricity mixes*. However, we only found

[1] We performed likelihood ratio tests for interaction effects (see Sawtooth Software Inc. 2021a) between the *electricity mix* and the *share of regional generation* in both samples, but did not find significant effects. Consequently, they were removed from the final models (see Hensher et al. 2005a, p. 664).
[2] For a discussion on the influence of covariates on parameter estimates, see, for example, Orme and Howell (2009). Samples size requirements in choice experiments are discussed, for example, in Bekker-Grob et al. (2015).

a positive effect of education on the *renewables mix* (1.214%), but this effect approaches zero for the *wind mix* (0.093%) and changes its sign to negative for the *solar mix* (-0.260%). The reasons for this may be manifold, e.g., that well-educated respondents are more likely to be aware that some diversity in generation technologies is beneficial, e.g. with respect to security of supply, land availability, visual impacts, etc. (see, e.g., Yang et al. 2016; Shmelev and van den Bergh 2016).

The results regarding community size are inconclusive: In the *Energiedienst* sample, the WTP for *50%* (*100%*) *regional generation* increases by 1.076% (2.163%) as community size decreases, i.e. respondents living in rural areas have a preference for regional generation. On the other hand, the effects of community size in the panel sample are close to zero and not significant. Hence, the hypothesis that the urban population prefers regional to non-regional generation cannot be supported. However, the large effect sizes in the *Energiedienst* sample suggest that, depending on the region, there may be differences between urban and rural populations within Germany. In summary, we find relatively little support for the hypothesis that female, young, well-educated and/or urban electricity customers have a higher WTP for *regional generation* (H2).

When looking at the price coefficient, income only has a marginal impact on price sensitivity: The income elasticities in the panel and *Energiedienst* sample indicate that price sensitivity increases (decreases) by 0.024% and 0.071%, respectively, when income increases (decreases) by 1%. A higher monthly advance payment also leads to a marginal and significant effect in the panel sample: price sensitivity increases (decreases) by 0.031% when the monthly advance payment increases (decreases) by 1%. These minor effects of income and price were to be expected, as electricity tariffs are a low-involvement product, which generally attracts little interest and awareness (see Layer et al. 2017). It is therefore likely that price sensitivity depends on other factors than income, such as attitudes (see Mewton and Cacho 2011). Furthermore, it cannot be assumed that an increase in income, either as a result of an actual increase in income or a decrease in price, will make end consumers equally willing to pay more for electricity tariffs, even if such tariffs have positive externalities.

Table 4: Results of the covariates analysis, sociodemographic characteristics, panel sample (N=838).

		δ^{Gender}		δ^{Age}		$\delta^{Education}$		$\delta^{CommunitySize}$		$\delta^{FederalStatePV}$		$\delta^{FederalStateWind}$		$\delta^{IncomeMiss}$		λ^{Income}		$\lambda^{PriceMonthly}$	
Attribute	Level	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ
Electricity mix	Default mix	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Renewables mix	1.336*	0.650	-0.590*	0.260	1.214^{+}	0.685	-0.262	0.274	-	-	-	-	-	-	-	-	-	-
	Wind mix	1.003	0.857	-0.730**	0.280	0.093	0.759	-0.383	0.315	-	-	0.846	0.540	-	-	-	-	-	-
	Solar mix	1.256	0.892	-0.789**	0.296	-0.260	0.702	-0.490	0.315	-0.260	0.359	-	-	-	-	-	-	-	-
Share of regional generation	0%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	50%	0.530^{+}	0.323	0.060	0.114	0.361	0.298	0.113	0.137	-0.333	0.380	-0.039	0.464	-	-	-	-	-	-
	100%	1.002*	0.431	-0.255^{+}	0.149	0.630	0.412	0.149	0.175	-0.092	0.396	-0.250	0.555	-	-	-	-	-	-
Price[a]	[100;115]	-	-	-	-	-	-	-	-	-	-	-	-	-0.053***	0.013	-0.024**	0.008	0.031**	0.010

[a] Continuous attribute in preference space, lognormally distributed.

p<0.10: +, p<0.05: *, p<0.01: **, p<0.001: ***, based on Bayesian inference (see Lenk 2014).

Table 5: Results of the covariates analysis, sociodemographic characteristics, *Energiedienst* sample (N=59)

		δ^{Gender}		δ^{Age}		$\delta^{Education}$		$\delta^{CommunitySize}$		$\delta^{IncomeMiss}$		λ^{Income}		$\lambda^{PriceMonthly}$	
Attribute	Level	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ
Share of regional generation	0%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	50%	0.793	2.598	0.256	0.775	2.159	2.085	1.076	1.022	-	-	-	-	-	-
	100%	5.479*	2.491	-0.442	0.811	0.952	2.491	2.163^{+}	1.251	-	-	-	-	-	-
Price[a]	[100;115]	-	-	-	-	-	-	-	-	0.167	0.149	0.071	0.047	-0.056	0.041

[a] Continuous attribute in preference space, lognormally distributed.

p<0.10: +, p<0.05: *, p<0.01: **, p<0.001: ***, based on Bayesian inference (see Lenk 2014).

While our model results confirm that sociodemographic characteristics have limited explanatory power, past behavior is a substantially stronger predictor (see Table 6).

Table 6: Results of the covariates analysis, past behavior, panel sample (N=838).

		$\delta^{Switched}$		$\delta^{CurrMix}$		$\delta^{CurrSupplierMES}$		$\delta^{CurrSupplierCES}$	
Attribute	Level	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ
Type of supplier	National energy supplier	-	-	-	-	-	-	-	-
	Municipal energy supplier	-	-	-	-	0.466^{+}	0.272	-	-
	Citizen energy supplier	-	-	-	-	-	-	7.079***	1.301
Electricity mix	Default mix	-	-	-	-	-	-	-	-
	Renewables mix	-	-	5.706***	0.860	-	-	-	-
	Wind mix	-	-	5.899***	0.900	-	-	-	-
	Solar mix	-	-	6.337***	1.004	-	-	-	-
Share of regional generation	0%	-	-	-	-	-	-	-	-
	50%	-	-	1.140***	0.349	-0.126	0.350	1.277	1.282
	100%	-	-	1.074***	0.452	0.261	0.463	0.761	1.363
Price[a]	[100;115]	0.065***	0.015	-	-	-	-	-	-

[a] Continuous attribute in preference space, lognormally distributed.

p<0.10: +, p<0.05: *, p<0.01: **, p<0.001: ***, based on Bayesian inference (see Lenk 2014).

Respondents who already purchase green electricity have a significantly higher WTP for the renewable *electricity mixes*, but also a slightly higher WTP for *regional generation*, with 1.140% (1.074%) for a *50%* (*100%*) *share of regional generation*. This indicates that H4 is true. In addition, these results give reason to believe that H6 is also correct, which will be examined in more detail.

Our model results also support H5: The price sensitivity of respondents who switched their electricity supplier or tariff in the past is 6.5% higher in the panel sample. This result is in line with the respondents' statements: 80.07% in the panel and 79.66% in the *Energiedienst* sample cited price savings as one motivation for switching the electricity supplier or tariff in the past. Only 18.18% and 38.10% cited switching to green electricity as (another) motivation. Therefore, it may be difficult for electricity suppliers to persuade customers to switch to a regional electricity tariff without monetary incentives (see also Ozaki 2011; Kaenzig et al. 2013; He and Reiner 2017).

There is reason to believe that this motivation to switch is higher among customers of municipal or citizen energy suppliers, as these customers are supposed to have a higher degree of environmental awareness and/or stronger regional ties as customers of *national energy suppliers* (see Chapter 3). However, H6 proves to be incorrect: although there is a positive WTP for the current *type of supplier*, which is particularly salient among customers of *citizen energy suppliers*, WTP does not differ between these customer groups with regard to the *share of regional generation*.

The results so far have only provided insights at an aggregate level. Based on the posterior means of the random WTP coefficients and the fixed effects covariates, the individuals' additional WTP $\omega^{Attributes}$ can be obtained (see Section 4.2). The empirical distribution functions of the individuals' WTP estimates are shown in Figure 2.[1] We find that (i) almost all respondents have a positive WTP for regional generation, (ii) which increases with the *share of regional generation*, and (iii) WTP is higher in the *Energiedienst* sample than in the panel sample. Yet, we also find that (iv) WTP is low in magnitude: Only slightly more than 30% in the *Energiedienst* sample and about 1% in the panel sample is willing to pay more than 5% price markup for *50% share of regional generation*. WTP for *100% regional generation* is higher, but still limited: Less than half of the respondents in the *Energiedienst* sample and even less than 10% in the panel are willing to pay 7.5% price markup. These results raise the question of whether WTP is even sufficient to cover the additional costs of regional electricity marketing. If this is the case, then it is essential to know which customer groups can be addressed with regional electricity tariffs. However, the effects of sociodemographics on WTP are small, but somewhat higher for past behavior. Importantly, there is a large variability in WTP, suggesting that different segments of customers differ in their preferences.

[1] The empirical distribution functions of the additional WTP in euros per month which result from multiplying the estimates in percentage by the monthly advance payment can be found in Figure 5 in the Appendix.

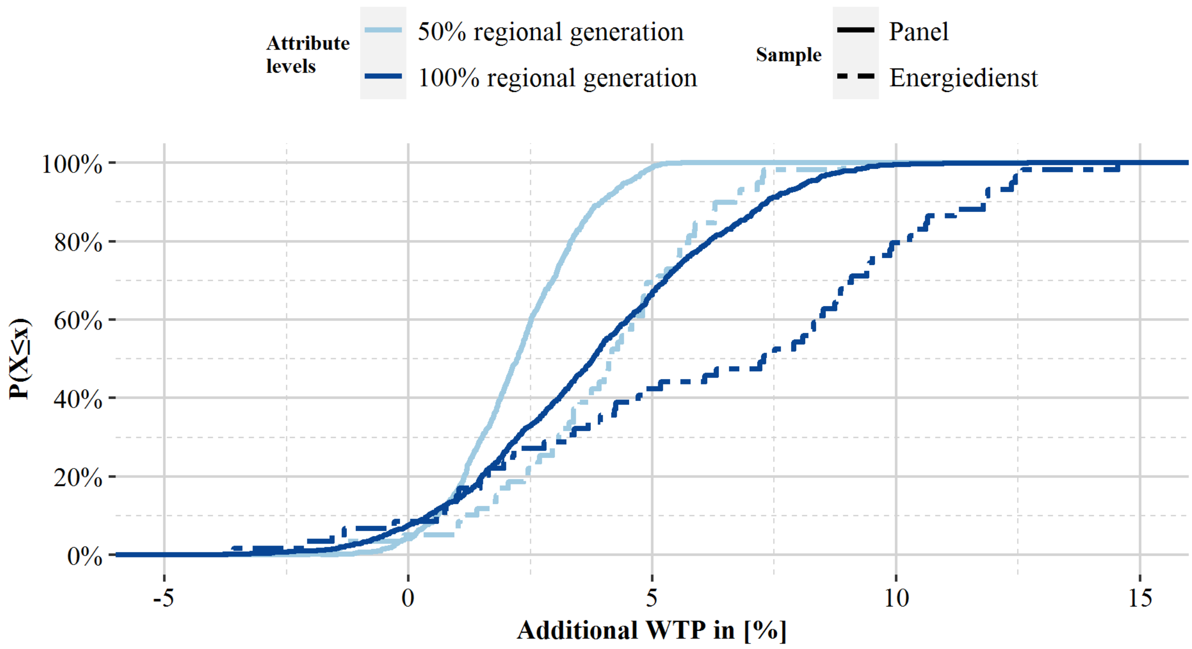

Figure 2: Empirical distribution functions of conditional WTP estimates (including covariates) of the panel sample (N=838) and Energiedienst sample (N=59).

5.3 Cluster analysis

To identify respondents with similar WTP and to test H7, i.e. whether regional electricity customers are a subgroup of green electricity customers, a cluster analysis is applied to the conditional WTP estimates in both samples. The Gaussian Mixture model (see Section 4.2) results in three clusters for the panel sample and one cluster for the *Energiedienst* sample using the Bayesian Information Criterion (BIC) by Schwarz (1978). The cluster centroids and sizes are shown in Table 7. Graphics of the clusters as pair plots can be found in Figure 6 and Figure 7 in the Appendix.

Table 7: Result of the cluster analysis using a Gaussian Mixture model for the panel sample (N=838) and *Energiedienst* sample (N=59). Cluster centroids expressed as additional WTP (in percent).

		Panel sample			Energiedienst sample
Attribute	Level	I	II	III	I
Type of supplier	National energy supplier	-	-	-	-
	Municipal energy supplier	0.874	1.863	1.757	6.597
	Citizen energy supplier	-0.462	7.181	0.126	5.466
Electricity mix	Default mix	-	-	-	-
	Renewables mix	2.479	14.655	12.899	24.010
	Wind mix	0.051	11.836	10.341	17.006
	Solar mix	0.835	14.368	11.895	19.857
Share of regional generation	0%	-	-	-	-
	50%	1.512	5.165	3.051	4.004
	100%	2.280	7.362	5.859	6.162
Cluster size [a]		496	8	334	59

[a] Assignment of respondents based on the highest class membership probability.

The cluster analysis shows a clear correlation between the WTP for green *electricity mixes* and the WTP for *regional generation*: Respondents who are hardly willing to pay a premium for green electricity are also hardly willing to pay a premium for *regional generation* (Cluster I), although WTP for both is about the same level. This is true for about 59% of the panel sample. The remaining respondents (Clusters II and III) show a moderate WTP for *regional generation* of up to 7.362% on average. In Cluster II, the high WTP for *citizen energy suppliers* is noteworthy, which has led to an extra cluster for these eight respondents. Other than that, the Clusters II and III are similar. In the *Energiedienst* cluster, WTP for *regional generation* is about the same as in Clusters II and III of the panel sample. However, *regional generation* seems to be a subordinate product attribute, at least compared to the renewable *electricity mixes*.

5.4 Portfolio simulation

To test whether the introduction of a regional electricity tariff leads to product cannibalization (see Baker and Hart 2007, p. 320), we conducted a market share simulation with product alternatives observable in the market (see Hess and Palma 2019, pp. 27–28). The expected probabilities of product alternatives can be interpreted as portfolio shares (Rossi et al. 2009, p. 3). In the base scenario, we chose a *national electricity supplier* for the panel sample and a *municipal energy supplier* for the *Energiedienst* sample that offers two non-regional electricity tariffs, respectively, one with a *default electricity mix* (*0% price markup*) and another with a *renewables mix* (*5% price markup*). In scenarios 1 and 2, a regional green electricity tariff is now added to the portfolios, with *50%* and *100% regional generation*, respectively. For these regional electricity tariffs, a *15% price markup* is charged in both samples, as offering regional green electricity requires the use of both registers, the GRO and the SGRO, resulting in costs exceeding those of green electricity only (see Lehmann et al. 2021). For model calibration, we used alternative-specific constants to adjust the portfolio shares in the base scenario to the relative shares of respondents purchasing grey and green electricity (see Hensher 2010). The results of the simulation are shown in Figure 3.

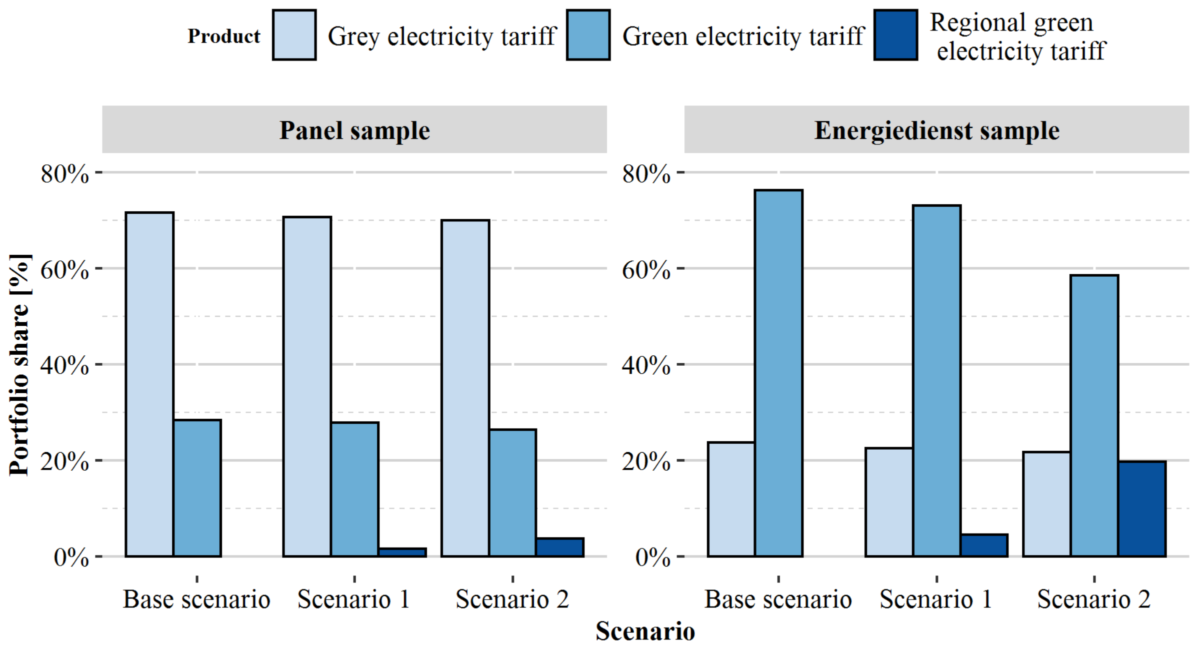

Figure 3: Result of the portfolio simulation in the base scenario (no regional electricity tariff), scenario 1 (regional electricity tariff 50%) and scenario 2 (regional electricity tariff 100%).

In the base scenario, 28.41% of the panel sample and 76.26% of the *Energiedienst* sample purchase green electricity, which reflects the actual shares in the samples. After adding a regional electricity tariff with *50% regional generation* (Scenario 1), this new product takes 1.53% and 4.50% portfolio share, respectively. If the *share of regional generation* is increased to *100%* (Scenario 2), the portfolio share increases to 3.64% and 19.74%. It is evident that the relative shares of the gray electricity tariff are almost unchanged across all scenarios, i.e. only the (potential) green electricity customers switch to the regional green electricity tariff. This supports H7, stating that regional electricity customers are a subgroup of green electricity customers. The simulation also shows that the *Energiedienst* sample is more amenable to regional electricity tariffs, i.e., managerial decisions regarding portfolio changes should take into account the respective customer base of an energy supplier.

6 Discussion

6.1 Key findings, implications and further research

The introduction of the "System for Guarantees of Regional Origin" (SGRO) by the German legislator enables energy suppliers to purchase electricity from subsidized generation facilities and to advertise regionality. However, whether and to what extent end customers are willing to pay for regional electricity is largely unclear. To address this gap, we surveyed a representative sample for Germany and a specific sample of an energy supplier operating in southern Germany.

Our model results show that, on average, regionality in electricity generation is perceived as a positive product attribute. Hence, WTP increases with the *share of regional generation*. Furthermore, WTP seems to have increased over the recent years (cf. Kaenzig et al. 2013; Kalkbrenner et al. 2017). In absolute terms, however, WTP for regional generation is (still) highly limited. Compared to the WTP for the *electricity mix*, i.e., for green electricity, WTP for regional generation is substantially lower, and only pertains to a subgroup of electricity customers. This circumstance turns out to be even more serious in the context of the current German regulatory framework, which limits the *share of regional generation* to the share of subsidized electricity (see paragraph 79a (8) EEG). Therefore, currently only about 50% of the electricity purchased can be reported as regional on a residential customer's end-of-year settlement. This may backfire on electricity suppliers and lead to trouble in explaining the product. On the other hand, if only a *50% share of regional generation* is advertised, the already low WTP is likely to be further eroded. From an energy supplier's perspective, this raises the question of whether WTP is even sufficient to cover the additional expenses incurred by regional procurement and marketing (see Lehmann et al. 2021). At least from a purely economic point of view, this is far from clear, although such a perspective does not take into account non-monetary gains, e.g. image improvements of energy suppliers, which might have a positive effects for these suppliers in the long run.

If an energy supplier decides to include regional electricity tariffs in its portfolio, marketing should target female, younger and better educated customers, although differences in WTP between these sociodemographic characteristics are relatively small. In contrast, there does not seem to be a difference between urban and rural populations, nor does income and the amount of the monthly advance payment for electricity have a substantial effect on price sensitivity. However, managers should keep in mind potential differences in the customer bases, which may lead to deviations from the German average preferences. Although *municipal energy suppliers* and *citizen energy suppliers* have an advantage over *national energy suppliers* in terms of congruence between product claims of regional electricity tariffs and corporate image (Lehmann et al. 2021), the current *type of supplier* does not seem to have a significant impact on WTP for *regional generation*. More relevant factors are the current type of electricity tariff, differentiated into green and non-green, but also the tariff switching behavior of the past. The latter is an indicator of high price sensitivity.

Our results further show that the potential target group for regional electricity tariffs is a subgroup of green electricity customers. As a consequence, the introduction of a regional electricity tariff is likely to lead to product cannibalization, meaning that mainly green electricity customers will switch their tariff. Again, whether this is economically viable for an energy supplier depends on the additional costs of regional procurement and marketing, i.e., whether margins are higher for regional green electricity tariffs than for green electricity tariffs.

Furthermore, results of previous studies show that switching behavior in electricity tariffs is characterized by great inertia (e.g., Kaenzig et al. 2013; Pichert and Katsikopoulos 2008; Yang et al. 2016). To overcome this inertia, customers need information on the positive effects of switching their tariff (Diaz-Rainey and Ashton 2011; Ozaki 2011), e.g. about supporting their region. From an energy supplier's perspective, however, this requires both funding of these positive effects and advertising expenses, which reduces margins. Justifying the price markup of regional electricity with additional costs on the procurement and sales side will hardly meet with any understanding from customers (Lehmann et al. 2021). Moreover, this inertia in switching the electricity tariff also limits the possibility to poach (satisfied) customers from competitors. An easier way may be to convince customers of regional electricity who want to switch anyway. Yet, this limits the potential for acquisition further.

Regionality in electricity tariffs is a fairly new product attribute. This may be one of the reasons for the current low WTP. For green electricity in Germany, it also took several years for demand to increase (see Hauser et al. 2019, p. 91). Therefore, further research is needed to identify factors that drive preferences and thus WTP for regional electricity. Given that sociodemographic characteristics do not seem to have a big influence on WTP for regional electricity, future research should consider other factors that allow to better understanding. Such characteristics could, for example, include customers’ psychological attachment to their region (see, e.g., Carrus et al. 2014) or their environmental motivations (see, e.g., Steg et al. 2015) and might provide a better understanding of the potential that regional electricity tariffs could achieve.

From a policy perspective, the SGRO was introduced to create new sales channels for subsidized electricity from renewables, but also to increase the acceptance of new installations. Our empirical analyses show that regionality in electricity generation is a product attribute of electricity tariffs that has gained in importance (cf. Kalkbrenner et al. 2017; Kaenzig et al. 2013), but is still of significantly lower importance than other product attributes. Hence, WTP is highly limited. This, in combination with the additional costs incurred by regional procurement and marketing, severely limits the potential of this new sales channel. Moreover, it remains unclear whether regional electricity can make a contribution to increasing local acceptance (as opposed to general acceptance, see, e.g., Sütterlin and Siegrist 2017). This is especially true since, in the current regulatory framework, regional electricity is marketed as a premium product with a price markup, leaving the local population uncompensated for potential visual impacts or land use.

6.2 Limitations

Of course, this study is not without limitations. Our WTP estimates are conditional, i.e., they are the result of forced choice situations (see Allenby et al. 2013). Therefore, these estimates do not have to coincide with unconditional WTP estimates in situations when people could simply stick to their current choice. For most real-life choice situations, the status quo, in this case the current electricity tariff, comes with a positive utility (see Samuelson and Zeckhauser 1988).

Since regional electricity tariffs are a fairly new product, there is also a risk that our respondents did not (fully) understand the attributes and levels in the choice experiment (see also Dütschke and Paetz 2013). However, we countered this risk with an adequate survey design (explanatory texts, info buttons, simple language, etc.), but the risk can never be completely ruled out (see Coast et al. 2012).

Furthermore, the choice situations in the surveys were hypothetical, which may have led to deviations from real-life behavior (so-called *hypothetical bias*). The main reason for hypothetical bias is usually a lack of incentive compatibility, i.e., there is no motivation for respondents to reveal their true preferences (see, e.g., Czajkowski et al. 2017; Beck et al. 2016). Other reasons for hypothetical bias may include the survey design and the product alternatives displayed (see, e.g., Reed Johnson et al. 2013; Murphy et al. 2005), respondents' personality (see, e.g., Grebitus et al. 2013; Wuepper et al. 2019; Menapace and Raffaelli 2020) or knowledge (see, e.g., Lusk 2003; Ready et al. 2010; Tonsor and Shupp 2011). The better a hypothetical choice situations simulates a real-life choice situation, the lower the hypothetical bias usually is (Louviere 2006). Most of the times, hypothetical bias has a negative impact on the WTP observable in the real market (see, e.g., Berrens and Little 2004; List and Gallet 2001; Murphy et al. 2005; Ready et al. 2010). On the other hand, it can be assumed that sales and marketing departments of energy suppliers will use emotions when launching regional electricity tariffs, which may have positive effects on WTP. For example, Fait et al. (2020) show that environmental priming increases the WTP for green electricity tariffs. However, we cannot be certain if WTP for real-life choices would be higher or lower than the estimates we find in this study. Therefore, our WTP estimates should be interpreted with caution in absolute terms, but implications on the marginal rates of substitution are usually still valid (Louviere et al. 2000a, pp. 17–18).

Two other limitations of our study are the channel of sample collection and sample sizes: Although web surveys have numerous advantages, especially for choice experiments, disadvantages include the difficulty of assessing sample quality (see Mariel et al. 2021, pp. 54–58). For example, self-selection bias may be present in both samples (see Bethlehem 2010). In line with previous studies, we also found that the effect sizes of sociodemographic covariates are small (e.g., Orme and Howell 2009; Hess 2014). These small effects, in combination with the limited sample size of the second survey, often resulted in non-significant parameter estimates. As a consequence, we had to limit our interpretation primarily to effect sizes rather than significances. Moreover, this limited sample size bears the risk of only having surveyed a subgroup of the actual customer base.

Finally, we find our results in the context of the German energy market regulation. It is possible that a general WTP for regional electricity exists in other countries as well, but future research should examine this.

CRediT author statement

Nico Lehmann: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration; **Daniel Sloot:** Conceptualization, Methodology, Writing - review & editing **Armin Ardone:** Conceptualization, Supervision, Writing - review & editing, Resources, Funding acquisition; **Wolf Fichtner:** Supervision, Writing - review & editing, Resources, Funding acquisition

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A. Appendix

Table 8: Studies on WTP for regional electricity generation in Germany.

		Sample						
Reference	Year	Size	Representativeness	Method[a]	Parameter space	Sociodemographic characteristics	Customer segmentation	Definition of regionality
Kaenzig et al. (2013)	2009	414	✓	CBC	Utility space	×	×	Region (undefined)
Kalkbrenner et al. (2017)	2014	953	×	CBC	Utility space	×	×	20 kilometer radius
Günther et al. (2019)	2018	663	×	CBC	Utility space	×	×	Existing wind farm
Fait et al. (2020)	2018	663	×	CBC	Utility space	×	×	Existing wind farm
Bengart and Vogt (2021)	Unknown	274	×	BWS	Utility space	×	×	50 kilometer radius
Current research	2019	838	✓	CBC	WTP space	✓	✓	50 kilometer radius

Included: ✓, Not included: ×
[a] Choice-based conjoint: CBC, Best-worst scaling: BWS

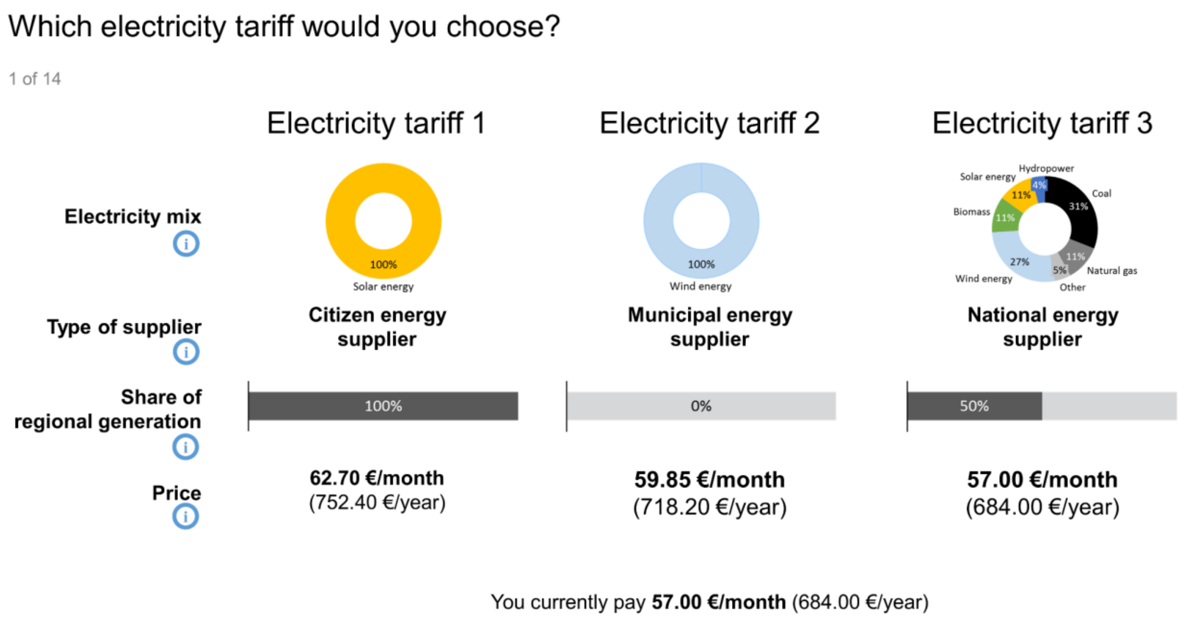

Figure 4: Exemplary choice set of a respondent with a monthly advance payment of 57.00 euros (texts translated from German).

Table 9: Sample characterizations and representativeness according to gik (2018).

	Panel sample (N = 838) Frequency (%)	Energiedienst sample (N = 59) Frequency (%)	Representativeness as defined by gik (2018) Frequency (%)
Gender			
Male	48.3	81.4	51.0
Female	51.6	18.6	49.0
Age			
18-29 years	22.5	8.5	21.0
30-39 years	15.7	23.7	18.0
40-49 years	19.6	13.6	21.0
50-59 years	23.6	27.1	23.0
60-69 years	18.6	27.1	17.0
Education			
Low: No degree or secondary school graduate	40.3	10.2	30.0
Medium: General certificate of secondary education	23.3	28.8	36.0
High: General higher education qualification or university degree	36.4	61.0	33.9
Household size			
1 person	19.7	11.9	21.0
2 persons	36.7	39.0	35.0
3 or more persons	43.6	49.1	44.0

[a] Own calculations

Table 10: Upper level model results for mean parameters for underlying normal distribution.

		Panel sample		Energiedienst sample	
Attribute	Level	post μ	post σ	post μ	post σ
Type of supplier	National energy supplier	-	-	-	-
	Municipal energy supplier	1.000***	2.436***	6.603***	6.501***
	Citizen energy supplier	-0.223	2.204***	5.473***	6.370***
Electricity mix	Default mix	-	-	-	-
	Renewables mix	4.405***	7.649***	24.009***	14.764***
	Wind mix	1.905**	9.382***	17.014***	11.044***
	Solar mix	3.024***	9.670***	19.861***	12.772***
Share of regional generation	0%	-	-	-	-
	50%	1.785***	1.930***	3.856***	3.205***
	100%	2.872***	3.627***	5.143***	5.009***
Price[a]	[100%;115%]	0.178***	0.252***	0.160**	0.281***

[a] Continuous attribute in preference space, lognormally distributed.
p<0.10: +, p<0.05: *, p<0.01: **, p<0.001: ***, based on Bayesian inference (see Lenk 2014).

Table 11: Description of the covariates.

	Name of the covariate	Level of measurement	Value range	Transformation	Description
Sociodemographics	Gender	Nominal scale	{0,1}	-	Gender, male (0), female (1)
	Age	Ordinal scale	[1,2,3,4,5,6]	Mean centering	Age in years, measured in six classes. • 18-24 (1) • 25-29 (2) • 30-39 (3) • 40-49 (4) • 50-59 (5) • ≥ 60 (6)
	Education	Ordinal scale	[1,2,3,4]	Logarithm, mean centering	Education, measured in four classes. • No degree or secondary school graduate (1) • General certificate of secondary education (2) • General higher education qualification (3) • University degree or higher (4)
	Income	Ratio scale	[500,8500]	Mean centering	Net household income, measured in euros.
	CommunitySize	Ordinal scale	[1,2,3,4]	Mean centering	Community size, measured in four classes. • > 100,000 citizens • 20,000-100,000 citizens • 5,000-20,000 citizens • < 5,000 citizens
	FederalStateWind	Nominal scale	{0,1}	-	Living in one of the three federal states with the largest installed wind capacity (Fraunhofer IEE 2019).
	FederalStatePV	Nominal scale	{0,1}	-	Living in one of the three federal states with the largest installed PV capacity (AEE 2019).
	PriceMonthly	Ratio scale	[20,350]	Mean centering	Monthly advance payment in euros.
Past behavior	CurrentSupplierMES	Nominal scale	{0,1}	-	Current supplier is a municipal energy supplier.
	CurrentSupplierCES	Nominal scale	{0,1}	-	Current supplier is a citizen energy supplier.
	CurrentMix	Nominal scale	{0,1}	-	Current electricity tariff is a green electricity tariff.
	TariffSwitched	Nominal scale	{0,1}	-	Switched electricity tariff in the past three years.

Table 12: Influence of covariates on the attribute levels.

		Type of supplier			Electricity mix				Share of regional generation			Price
	Name of the covariate	National energy supplier	Municipal energy supplier	Citizen energy supplier	Default mix	Renewables mix	Wind mix	Solar mix	0%	50%	100%	[100, 115]
Sociodemographics	Gender					x^{P}	x^{P}	x^{P}		$x^{P,E}$	$x^{P,E}$	
	Age					x^{P}	x^{P}	x^{P}		$x^{P,E}$	$x^{P,E}$	
	Education					x^{P}	x^{P}	x^{P}		$x^{P,E}$	$x^{P,E}$	
	Income											$x^{P,E}$
	CommunitySize					x^{P}	x^{P}	x^{P}		$x^{P,E}$	$x^{P,E}$	
	FederalStateWind						x^{P}			x^{P}	x^{P}	
	FederalStatePV							x^{P}		x^{P}	x^{P}	
	PriceMonthly											$x^{P,E}$
Past behavior	CurrentSupplierMES		x^{P}							x	x	
	CurrentSupplierCES			x^{P}						x	x	
	CurrentMix					x^{P}	x^{P}	x^{P}		x^{P}	x^{P}	
	TariffSwitched											x^{P}

^{P} Covariate in the panel sample.

^{E} Covariate in the *Energiedienst* sample.

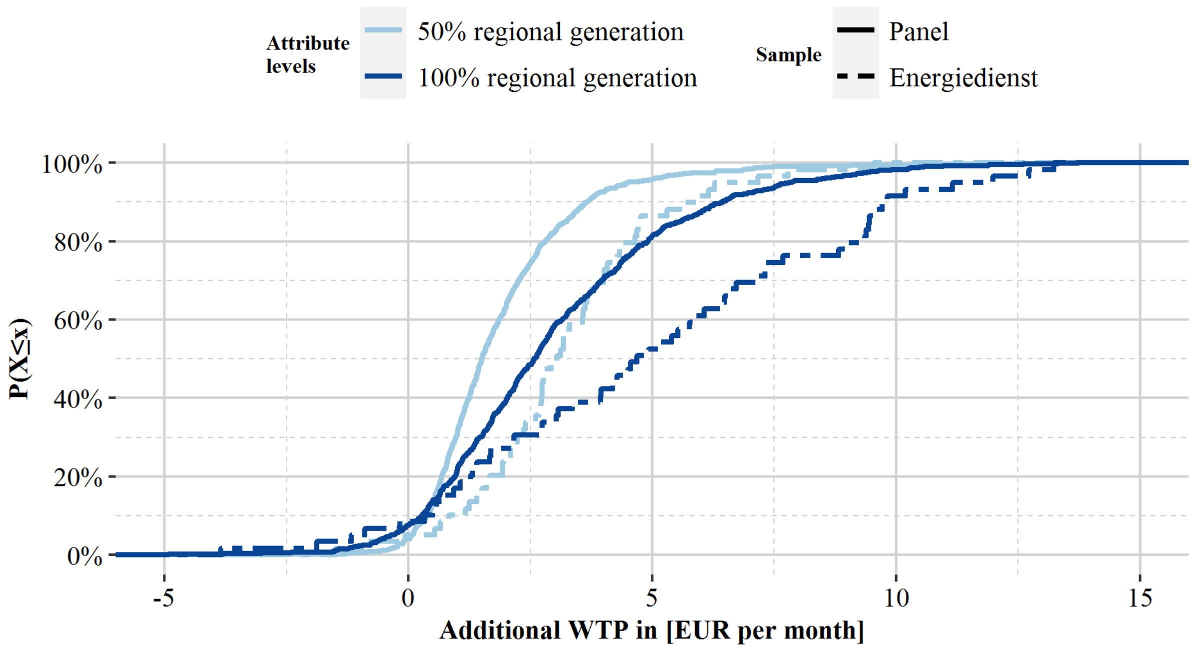

Figure 5: Empirical distribution functions of conditional WTP estimates (in euros per month, including covariates) of the panel sample (N=838) and Energiedienst sample (N=59).

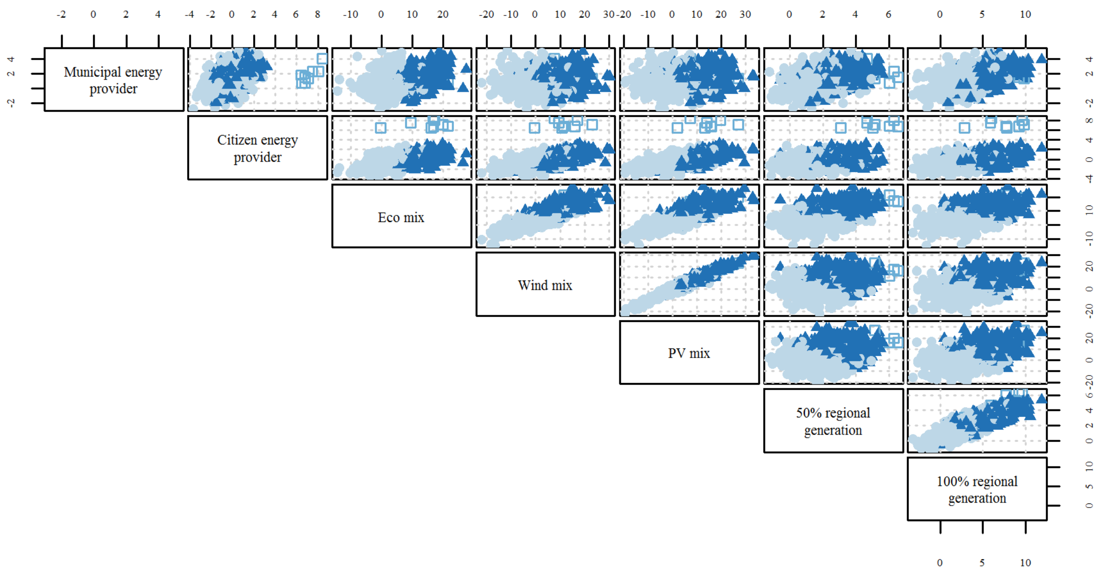

Figure 6: Result of the cluster analysis of the WTP values (in percent, including covariates) using a Gaussian Mixture model and three classes for the panel sample (N=838).

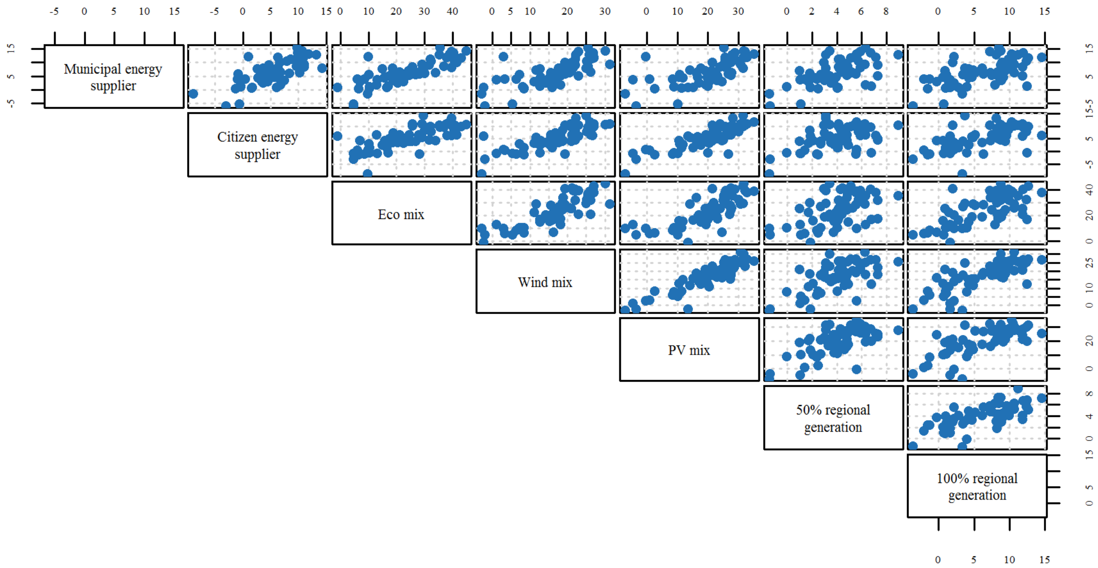

Figure 7: Result of the cluster analysis of the WTP values (in percent, including covariates) using a Gaussian Mixture model and one class for the *Energiedienst* sample (N=59).

B. Supplementary material

I. Results of the grid search

To estimate the MIXL models, we performed random samplings from the conditional distribution in two phases, the burn-in phase and the estimation phase (see Johnson 2000), with 100,000 and 500,000 draws, respectively. To reduce autocorrelation of the Markov chains (see Gelman et al. 2014; Rossi et al. 2009, p. 51), in phase two only every tenth draw was used for estimation (Train and Weeks 2005, p. 7). We set the priors for the means to zero, used an inverse Wishart distribution with ν degrees of freedom and scale matrix T for the covariance matrix (see Akinc and Vandebroek 2018), and allowed for full correlation (for a discussion on patterns of correlation, see, e.g., Hess and Train 2017; Carson and Czajkowski 2019). As optimal starting values for ν and T are dependent on the number of respondents and attributes, we followed Orme and Williams (2016) and performed a grid search with $\nu = \{2, 5, 10, 30\}$ and $T = \{0.5, 1.0, 1.5, 2.0\}$. The grid search resulted in optimal values, measured by the average log-likelihood value after burn-in, with $\nu = 30$ and $T = 1.0$ for the panel sample and $\nu = 10$ and $T = 2.0$ for the smaller *Energiedienst* sample. The results of the grid search can be found in Table 13.

To test internal and external validity, we calculated the HIT rate, both for the twelve choice tasks used for model estimation and for the two holdout tasks. The HIT rate measures the percentage of correct predictions in a given data set (Louviere et al. 2000b, p. 56). The internal (external) HIT rates of the panel and *Energiedienst* sample are 86.3% (69.5%) and 89.7% (67.8%), respectively. Compared to the naive model with a HIT rate of 33.33%, which results from repeated guessing which of the three alternatives will be chosen, these results indicate a good model fit. The HIT rates of the models with differing degrees of freedom ν and scale matrix T can also be found in Table 13.

Table 13: Results of the grid search.

			Panel sample			Energiedienst sample		
Model no.	PV	DF	LL	HR^{i}	HR^{e}	LL	HR^{i}	HR^{e}
1	0,5	2	-4.242,849	0,858	0,700	-252,070	0,863	0,686
2	0,5	5	-4.213,794	0,860	0,699	-246,230	0,877	0,678
3	0,5	10	-4.196,024	0,861	0,699	-243,708	0,895	0,669
4	0,5	30	-4.155,507	0,863	0,695	-254,923	0,897	0,644
5	1	2	-4.242,117	0,858	0,701	-256,413	0,860	0,661
6	1	5	-4.209,321	0,860	0,695	-248,368	0,879	0,678
7	1	10	-4.194,652	0,861	0,697	-245,068	0,895	0,669
8	1	30	**-4.145,949**	0,863	0,6945	-253,122	0,898	0,653
9	1,5	2	-4.240,180	0,858	0,697	-255,963	0,864	0,669
10	1,5	5	-4.211,106	0,860	0,699	-248,280	0,883	0,678
11	1,5	10	-4.191,761	0,861	0,696	-245,391	0,897	0,669
12	1,5	30	-4.150,862	0,863	0,694	-253,906	0,898	0,644
13	2	2	-4.235,872	0,858	0,697	-258,129	0,867	0,686
14	2	5	-4.210,177	0,859	0,699	-246,359	0,874	0,669
15	2	10	-4.201,423	0,860	0,698	**-243,645**	0,897	0,678
16	2	30	-4.159,773	0,862	0,696	-254,461	0,900	0,653

PV: prior variance, DF: degrees of freedom, LL: log-likelihood, HR: HIT rate
^{i} internal validity, ^{e} external validity

II. Histograms and kernel density estimates

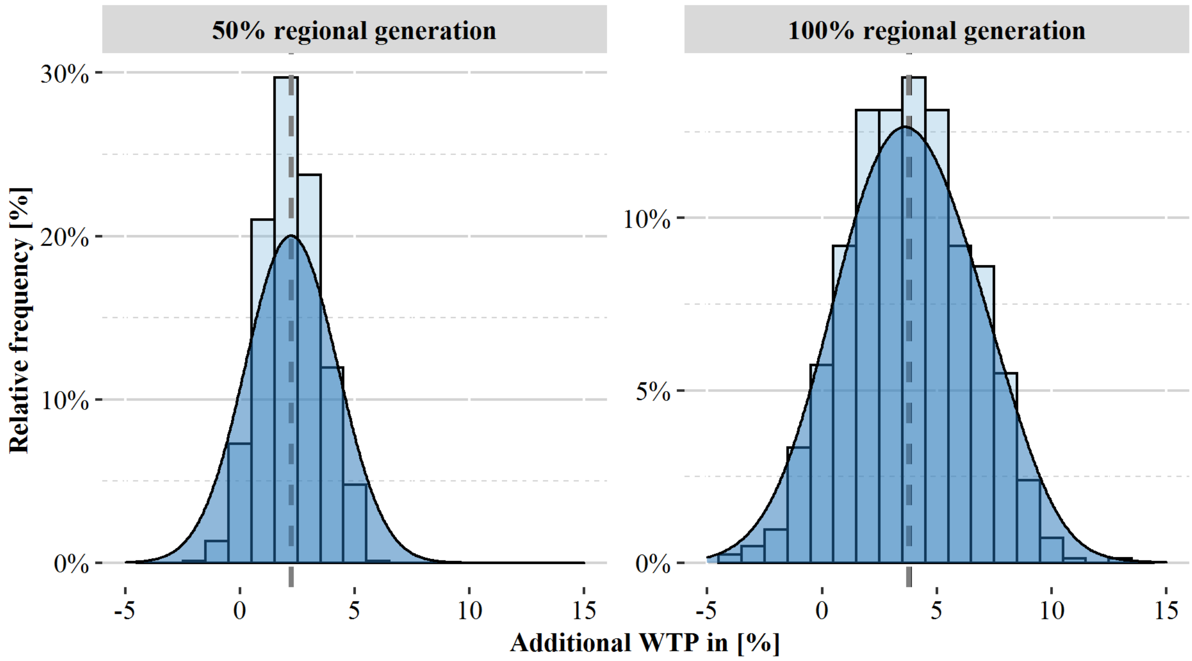

Figure 8: Histograms and kernel density estimates of the conditional WTP values (in percent, including covariates) of the panel sample (N=838). The black and gray vertical lines represent the mean and median, respectively.

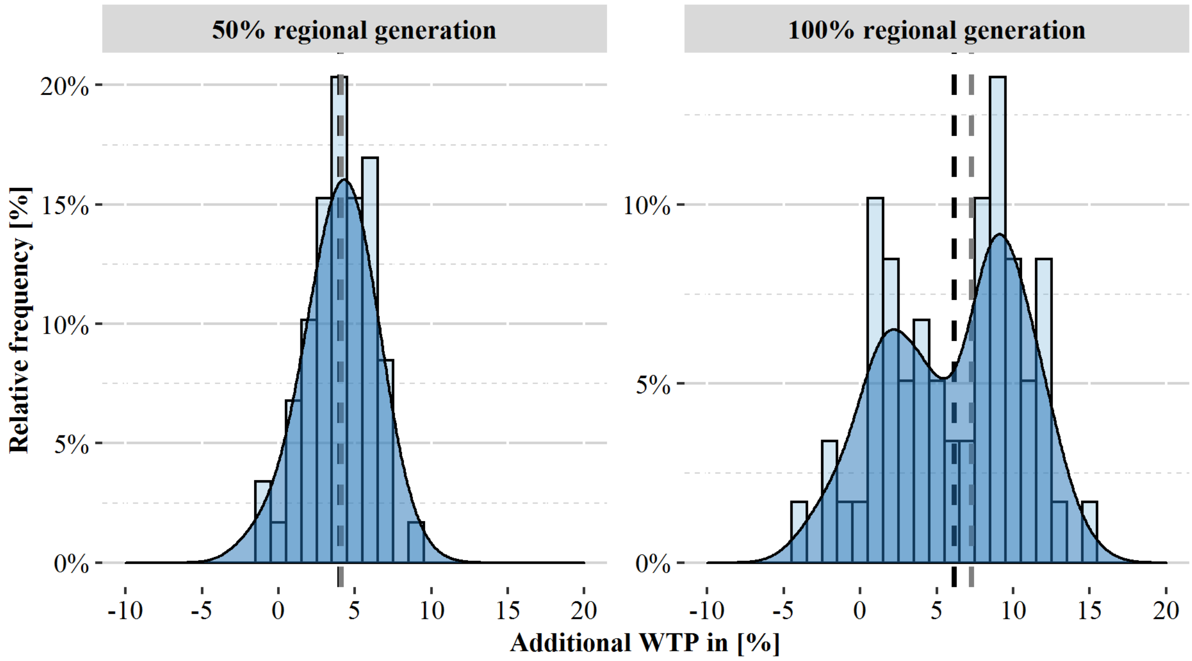

Figure 9: Histograms and kernel density estimates of the conditional WTP values (in percent, including covariates) of the *Energiedienst* sample (N=59). The black and gray vertical lines represent the mean and median, respectively.

III. Awareness regarding the attributes

Since regionality in electricity tariffs is a fairly new product attribute, respondents were asked in the first part of the survey (after a brief explanation of the CBC attributes) if they (i) knew about the respective attribute already before the survey and associated it with electricity tariffs immediately, (ii) had the knowledge before but only associated the attribute with electricity tariffs after it had been mentioned, (iii) just got the knowledge in the survey, or (iv) did not understand the attribute even after explanation. The results show that the awareness is highest for the *electricity mix* in both samples, meaning that a large proportion had the knowledge about this attribute already before the survey and some respondents even associated it with electricity tariffs immediately. By contrast, the different *types of energy suppliers* must at least be mentioned or even be explained. The same applies to the *share of regional generation*. Especially in the panel sample, respondents are mostly unaware of the distinction between regional and non-regional electricity (see Figure 10). In general, awareness is higher in the *Energiedienst* sample, which is not surprising since participation was voluntary, hence attracting more energy interested persons.

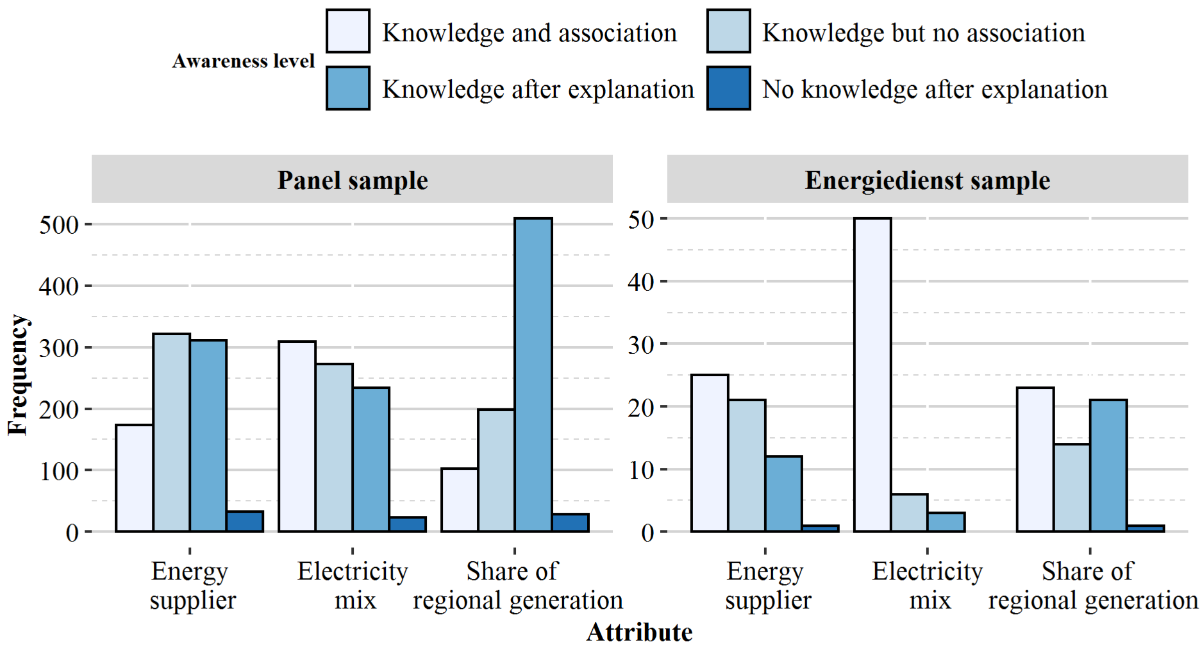

Figure 10: Bar chart of knowledge about the attributes and their immediate association with electricity tariffs for the panel sample (N=838) and the Energiedienst sample (N=59).

Since preferences, and thus WTP, may be driven by the awareness for an attribute, we tested for statistical correlation between the awareness for an attribute and the respondents' WTP. For both *shares of regional generation*, *50%* and *100%*, a Bayesian regression model for ordinal predictors by Bürkner and Charpentier (2020) was estimated. However, we only found a statistically significant relationship in the panel sample (see Figure 11), with little explanatory power and major parts of the variance left unexplained, especially at the lowest level of awareness. As a result, it can be concluded that factors other than the awareness drive WTP for *regional generation*. In the *Energiedienst* sample, the relationship between the awareness and WTP is insignificant (see Figure 12). As a result, it can be concluded that factors other than the awareness drive WTP for *regional generation*. It should be noted, however, that we measured the awareness with only one item, so measurement errors may be present (see, e.g., Liu et al. 2017).

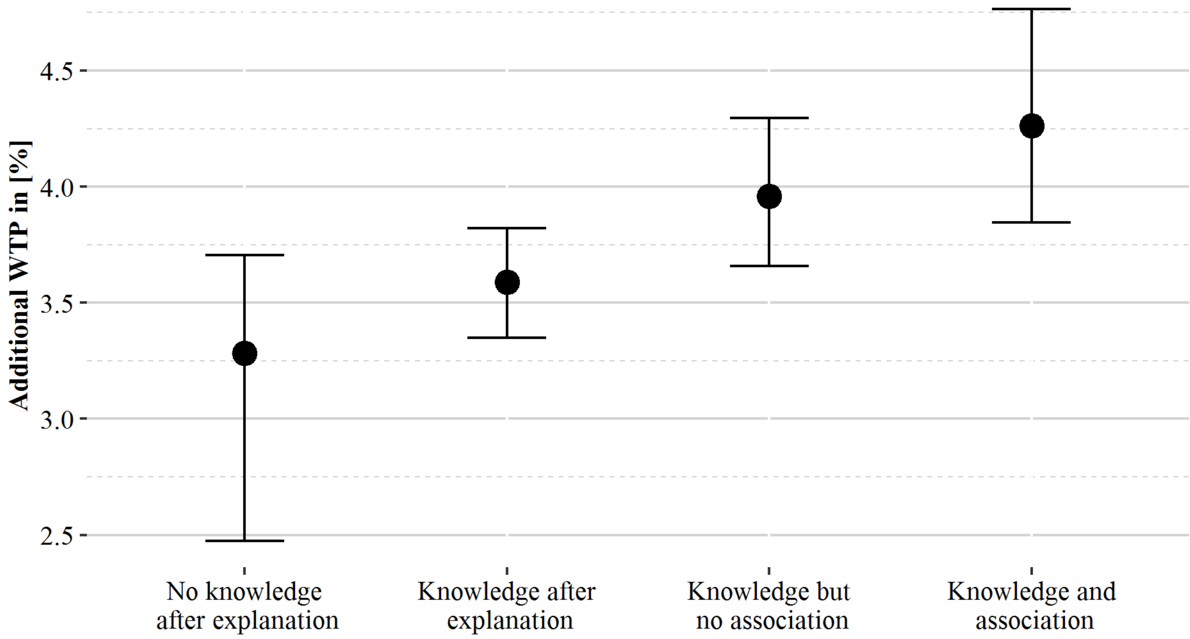

Figure 11: Results of the Bayesian regression model for *100% share of regional generation* for the panel sample (N=838).

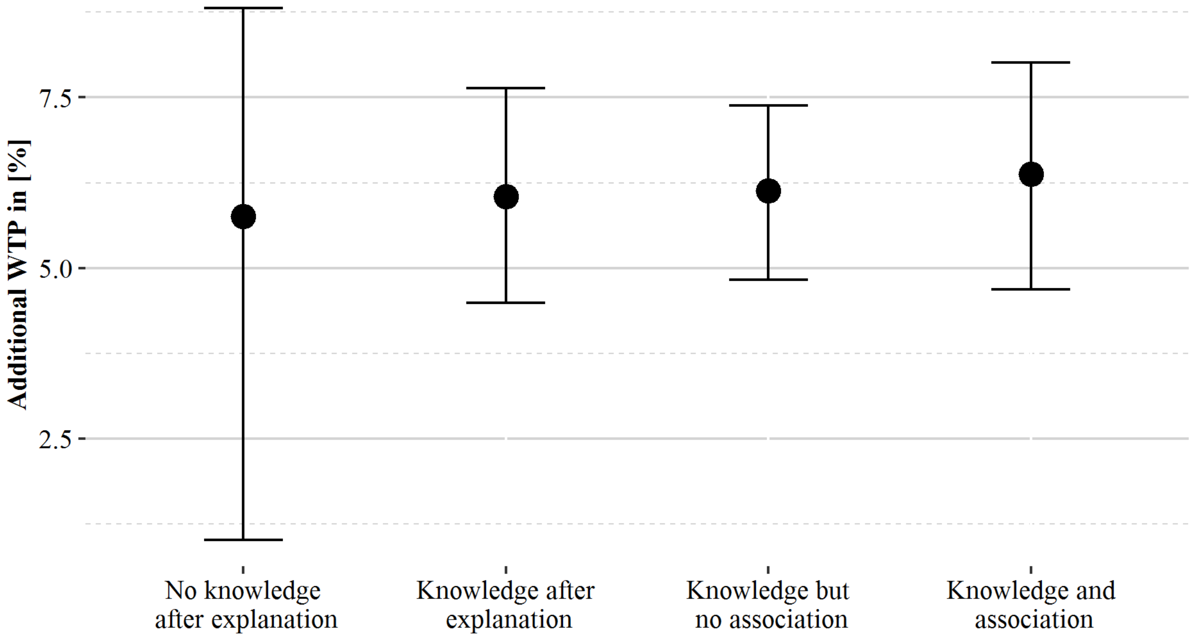

Figure 12: Results of the Bayesian regression model for *100% share of regional generation* for the *Energiedienst* sample (N=59).

IV. Attribute non-attendance

Choice experiments are based on Lancaster's (1966) theory of consumer behavior and usually on McFadden's (1974) random utility theory. The theory of consumer behavior postulates that the utility of an alternative results from its attributes, while the random utility theory assumes that a person always chooses the alternative that gives him or her the highest utility, supplemented by an error term that explains deviations from optimal choices. Empirical studies have shown that these basic assumptions are not always correct or do not apply to all respondents, leading, e.g., to biased parameter estimates and reduced model fit (see, e.g., Hensher 2014; Louviere et al. 2000b, p. 95).

In choice experiments, respondents may use heuristics such as lexicography, attribute non-attendance, elimination by aspects or selection by aspect (for a brief overview, see, Mariel et al. 2021, pp. 87–89). To obtain an indicator of which attribute levels tended to be ignored in the choice tasks, we followed the approach by Hess and Hensher (2010) and used the conditional parameter estimates to obtain the coefficients of variations. The higher the coefficient of variation of an attribute, the higher the probability that a respondent ignored a certain attribute level in the choice process. We chose a value of two as threshold. The results, plotted as empirical distribution functions, are shown in Figure 13 and Figure 14.

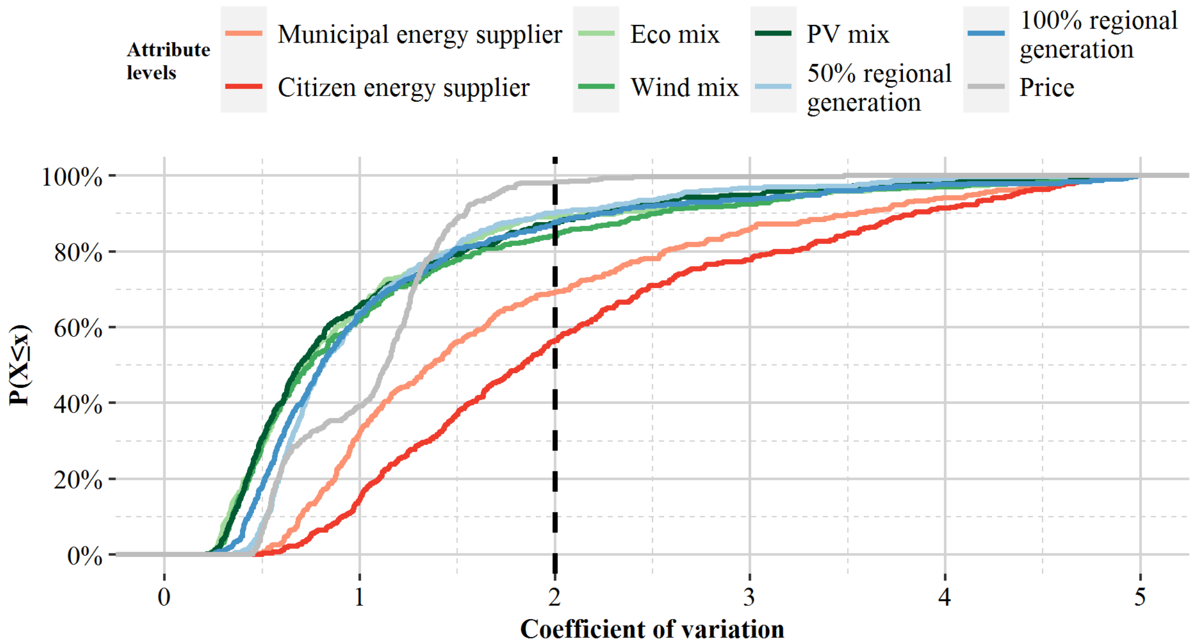

Figure 13: Empirical distribution functions of the coefficient of variation based on the conditional WTP values for the panel sample (N=838). The dashed black vertical line represents the threshold. Model without past behavior as covariates.

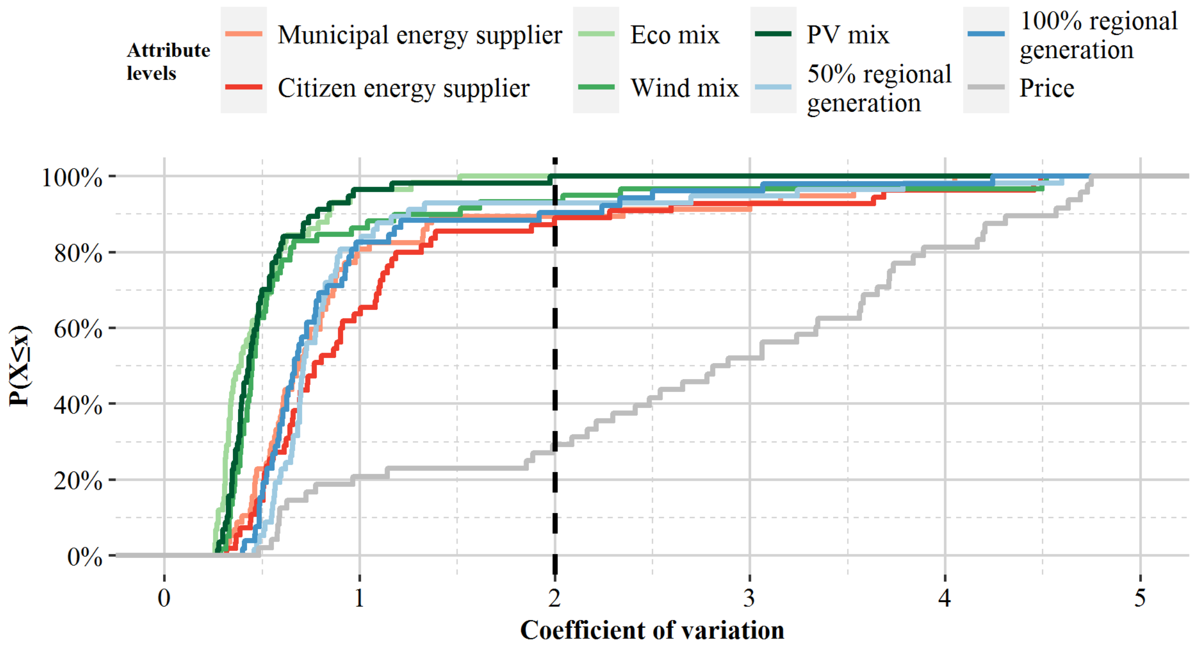

Figure 14: Empirical distribution functions of the coefficient of variation based on the conditional WTP values for the *Energiedienst* sample (N=59). The dashed black vertical line represents the threshold. Model without past behavior as covariates.

It emerges that in the panel sample, hardly any respondent ignored the *price* attribute (1.671%), but the *type of energy supplier* was frequently ignored, especially the *citizen energy supplier* level (40.334%). The *share of regional generation* and the *electricity mix* were ignored much less frequently, at less than 20%. By contrast, the *Energiedienst* sample shows a different picture: 76.271% ignored the *price* attribute, but less than 17% ignored the other attributes. This may be caused either by actual price insensitivity or by hypothetical bias, with the latter being more likely.