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Institute for Future Energy Consumer Needs and Behavior (FCN)

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Willing to Pay? Spatial Heterogeneity of e-Vehicle Charging Preferences in Germany

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Abstract

In this paper, we spatially map the willingness to pay for e-vehicle charging options according to the availability of public charging spots. We combine a Discrete Choice Experiment on charging preferences with a data set of public charging spots. Our results show spatial heterogeneity, i.e. respondents' choices depend on the quantity of public charging spots available to them. Non-availability of public charging spots in the vicinity has a larger effect on the choice probability than 1, 2, or 3 charging spots have. This could be evidence for charging infrastructure awareness. For the charging locations, we find marked spatial heterogeneity in the willingness to pay subject to the number of available public charging spots. The interaction of charging location with the number of public charging spots reveals a strong preference for charging at home rather than at work or charging on the road. However, with every additional public charging spot, respondents are more likely to charge away from home. This holds until the number of charging spots has reached a tipping point at which respondents become indifferent between home and work charging. When the tipping point is exceeded, respondents rather charge at work than at home. Thus, with increasing numbers of charging spots, public chargers near home are less relevant than those near work. Eventually, public chargers away from home become more attractive. Also, with increasing numbers of charging spots our results reveal a fivefold greater willingness to pay for reducing waiting time (for a charging spot to become available) than for accelerating charging speed. Thus, charging point operators could surcharge by implementing a booking scheme than by implementing fast-charging. From the findings, we derive further implications for charging infrastructure policy, business models, and infrastructure planning, e.g. regarding the expected break-even points for rolling out charging infrastructure and the provision of green energy.

Keywords: Electric mobility charging behavior, Charging spot awareness, Discrete Choice Experiment, Econometric modeling, Willingness to pay, Germany

JEL Classification: C25, D12, M38, Q58, R40

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1. Introduction

In economics, electric vehicle (EV) charging spots – a spatial combination of parking and refueling – are rival goods (Wolbertus et al. 2018a). A better fit of EV charging supply to user expectations, needs, and behavior has yet to be found (Daina et al. 2017; Wolbertus et al. 2018a). This, in turn, hinders the uptake of EV diffusion (chicken-and-egg problem). Further, users' *actual* EV charging spot usage may differ from previously anticipated *perceived* usage. Thus, the efficient alignment between the spatially heterogeneous supply of EV charging spots and (perceived) demand calls for a better understanding of private EV users' *expected* as well as *actual* recharging behavior. This study attempts to find out the perceived usage of charging infrastructure service as well as the willingness to pay (WTP) for them according to the number of currently available charging spots.

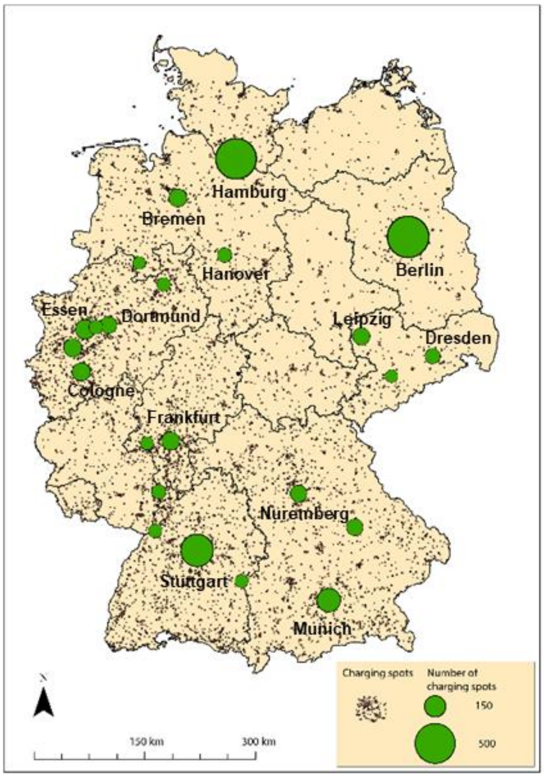

Figure 1: Distribution of charging spots across the 16 German Federal States with clusters in urban agglomerations marked in green. Source: ChargeMap.com (2019), own illustration, as of October 2019.

In Germany, the current EV share is just 0.28% out of 47.7 million passenger cars in total (as of January 1, 2020: Federal Motor Transport Authority 2020). The demand of 136,617 EVs for refueling at 18,838 public charging spots with 59,643 power outlets – a ratio of around 2.29 EVs per power outlet on average – seems sufficient for reducing range anxiety to an acceptable level (as of March 19, 2020: ChargeMap.com 2020). Yet, as expected, these charging spots are unequally distributed across the 16 federal states (Figure 1), partly reflecting the spatially heterogeneous EV diffusion patterns and population densities. Thus, balancing the spatial supply of and (perceived) demand for charging infrastructure efficiently is imperative for overcoming the chicken-and-egg problem and a successful sustainable mobility transition.

In Germany, up until now, EV infrastructure investment needs are high, and yet, the revenue streams are often still way too low even in the presence of the, by European and worldwide standards, relatively high electricity prices in the residential sector of about 0.29 €/kWh. Therefore, it is important to estimate the expected profitability of charging infrastructure projects (Schroeder and Traber 2012; Gnann et al. 2018; Madina et al. 2016). Also, it is not clear who should establish and run the EV charging infrastructure and whether any subsidization can indeed be justified from a social welfare perspective. Charging infrastructure operators could be car manufacturers, state-level or federal administration (or some governmental agency), municipalities, or energy companies. Consequently, for policy-making and planning purposes, it is crucial to better understand the diffusion patterns and the charging preferences of current and potential future EV drivers. Many studies find that the regular charging locations at home and at work are the most popular charging locations (e.g., for increasing EV purchase intention: Franke and Krems (2013), Bailey et al. (2015); employing choice experiments and surveys: Skippon and Garwood (2011), Chakraborty et al. (2019); and using EV field trials and data logging: Franke and Krems (2013), Björnsson and Karlsson (2015)).

Few studies have so far determined the spatial development of and need for charging infrastructure. Wolbertus et al. (2018a) analyze the determinants of charging session length while differentiating between connection time and total occupancy time (dwelling time) in the Netherlands. Depending on the EV range, Chakraborty et al. (2019) determine home and at-work charging to be the most requested charging locations. Interestingly, the density of charging spots plays a minor role compared to duration (Globisch et al. 2019). The demand side – determined by the EV charging behavior – has been analyzed for Germany by Soylu et al. (2016), Gnann et al. (2018), Wirges et al. (2012), Funke et al. (2019), and Wolff and Madlener (2019) but has not been contrasted with the actual supply of charging infrastructure and recent trends. Depending on the number of public charging spots available, this study finds charging preferences of current and potential future EV drivers and calculate the WTP, i.e. a reduction of the charging duration by 1 min is worth X Euros to consumers. Thus, to the best of our knowledge, this study is the first of its kind to spatially map the WTP for different attributes of the charging process in correlation to the available public charging infrastructure. More importantly, we identify spatial heterogeneity in the WTP for charging location subject to charging spots available in those regions. From that, we derive implications for charging infrastructure planning, e.g. regarding the expected break-even points for rolling out charging infrastructure and the provision of green energy. Thus, our results could be useful for charging infrastructure operators.

Therefore, our three research questions are: (1) Does the number of charging spots affect the preferences of individuals regarding specific characteristics of the EV charging process? (2) Depending on the number of charging spots, what is the WTP for certain attributes of the EV charging process? For example, how much are consumers willing to pay for an additional charging spot? How much is 1 minute less in charging duration worth? Following from that: (3) What are the implications for charging infrastructure policy, business models, and infrastructure planning with consideration of the spread of charging infrastructure?

Due to the low number of current EV users in Germany, investigating consumers' EV charging infrastructure preferences and their WTP for it based on real usage data is challenging. Therefore, we conducted an online Discrete Choice Experiment (DCE) to elicit preferences from existing EV users as well as non-users. The distinctive approach of this study is that we subsequently combined the choice data (and demographics) with locally available public charging spots. The present paper is based on the DCE data set also used in Wolff and Madlener (2019) but focuses now on charging spot availability and the resulting heterogeneity in WTP, rather than average WTP values.

The remainder of this paper is structured as follows. Section 2 introduces the reader to the discrete choice experiment. The results of the discrete choice modeling and WTP values derived are reported in Section 3 and discussed in detail in Section 4. Section 5 concludes.

2. Methods

2.1 DCE Design

Due to the previously mentioned low share of current EV users in Germany, and the variety of charging infrastructure operators, analyzing EV users' preferences for privately-used charging infrastructure services, their WTP for such services, and their interaction with existing charging infrastructure based on real usage data, is challenging. For our study, we gathered data through a Discrete Choice Experiment (DCE) conducted online in Germany (N = 4,101) (see also Wolff and Madlener, 2019). A DCE consists of hypothetical choice sets where the participants repeatedly choose between choice alternatives A and B. We asked respondents to imagine that they use an EV in their daily routines and that the range of the e-car is sufficient for their daily driving needs. We then asked them to imagine how and where they would like to charge the EVs' battery (under the assumption of a generic EV that is identical with respect to size, range, motor power etc.) and to choose 12 times in a row between two choice alternatives where attributes varied in their levels (Table 1).

The choice alternatives are described by six attributes found to be the most important and intuitive ones: (1) charging location; (2) charging duration (full charge); (3) charging technology; (4) waiting time for charging spot to become available; (5) share of renewables in the electricity mix used for charging; and (6) total cost for the full bundle of attributes per month. These attributes are defined by levels that vary randomly between choice scenarios, e.g., charging duration takes on either one of the four levels 10 min, 30 min, 4 h, or 8 h (Table 2). We chose values that can be considered as realistic within the next 5-10 years.

The DCE has a randomized design, i.e. when the respondents are repeatedly confronted with the choice scenarios with varying attribute levels, the attribute levels appear randomly with the limitation that at-home charging always has a waiting time of 0 min. The design algorithm ensures that all levels appear on the same number of choice cards. This design allows us to account for differences between individual choice behavior, since the respondents maximize their utility by choosing a particular charging solution that represents their individual trade-offs between attributes and choices. We did not include the choice alternative “None of the two options A and B” because for being able to drive the EV, users have to charge it somehow somewhere. One advantage of not including “None of the two” is that participants are required to consider their individual trade-offs and decide between options A and B. Hole (2007) calls this the Random Utility Maximization. We wanted to induce participants to trade-off between the choice alternatives, especially those respondents who might be opposed to e-mobility, in order to gain unbiased behavioral data.

We use conditional logit models, including fixed effects at the participant level, to exploit the repetitiveness of choices and, subsequently, follow Hole (2007) to calculate the WTP, i.e. the amount respondents are willing to pay for additional units of the attribute and the corresponding confidence intervals. By this means, we are able to estimate the effect of different factors on choice probabilities and narrow down the WTP for different features of the EV charging infrastructure and further preferences for EV charging.

2.2 Data Set on Existing Charging Spots

We use a data set of 6,264 zip code areas with 16,356 public charging spots (ChargeMap.com 2019)[1]. In our study, it is unclear if and to what extent the respondents are aware of the charging possibilities in their proximity. We call this *charging point awareness*. We use the number of charging spots per consolidated zip code area as a proxy for charging point awareness: the more charging points there are, the more likely it is that respondents have actually seen them in their area. Bailey et al. (2015) found evidence for charging point awareness using two concepts: “perceived charger *existence* as having seen a public charger in at least one location type, and perceived charger *abundance* as having seen […] chargers in at least two location types, e.g. at a workplace and in a mall.” Further, they define *public* charging as any location other than home, e.g. workplace and commercial charging locations. Carley et al. (2019) and Globisch et al. (2019) found that awareness of public charging point availability might positively influence EV purchase and lease intentions for both early as well as late adopters. Illmann and Kluge (2019) analyze charging preferences in terms of visibility, capacity and abundance of charging infrastructure and describe the *visibility effect* simply as ‘attention arousing’ because charging spots usually are designated to prominent locations, e.g. closest to the buildings or roads, usually in bright colors.

[1] A more official list offered by the German governmental body Federal Network Agency (2019, as of October), gives 10,556 charging spots offering 20,704 charging outlets. We consider this official list as incomplete because of larger figures given by ChargeMap.com (2019).

Table 1: Example of a choice card

Charging location	At home	At work
Charging duration (full charge)	10 min	4 h
Charging technology	Tethered charging (with cable)	Inductive charging (without cable)
Waiting time for available charging spot	0 min	30 min
Share of renewables	25%	75%
Charging cost per month	€5	€150
	◯ Choice A	◯ Choice B

Source: Wolff and Madlener (2019), p.5.

Table 2: EV charging infrastructure attributes and levels

Charging location: Location where you would like to charge most of the times. For *at home*, assume that the necessary charging infrastructure is at your disposal at your home. For *at work*, assume that the necessary charging infrastructure is at your disposal at your work place. *Roadside* means charging in a public space; e.g. in the city quarter or at the supermarket. Here we differentiate between *Roadside: main goal* and *Roadside: side activity*. *Roadside: main goal* means that you choose a particular charging spot and drive there with the sole goal of charging your car. The search for a charging spot is an end in itself, similar to the search of a gasoline spot. *Roadside: side activity* means that you happen to charge at a charging spot at the supermarket or during your leisure time (fitness studio etc.). Charging is a by-product.	At home	At work	Roadside: main goal	Roadside: side activity
Charging duration: Duration it takes to fully charge the battery of the electric car.	10 min	30 min	4 h	8 h
Charging technology: With *tethered charging*, you manually connect the electric car with a cable to the charging spot. With *inductive charging*, you park the electric car at a specific position at the charging spot. The charge process takes place automatically and without a cable.	Tethered charging (with cable)		Inductive charging (without cable)	
Waiting time for available charging spot: Public charging spots can be occupied by other cars. *Waiting time* gives you the time you have to wait until the spot becomes available for you. At-home charging is always paired with a waiting time of 0 min. Otherwise, combinations appear randomly.	0 min	5 min	10 min	30 min
Share of renewables: Share of renewables (wind or solar energy) in the electricity mix used for charging. This could be electricity produced in your own photovoltaic system on your roof top or green electricity mode available at public charging spots.	25%	50%	75%	100%
Charging cost per month: Total costs for the full bundle of attributes per month.	€50	€100	€150	€200

Source: Wolff and Madlener (2019), p.5.

2.3 Model Specification

We adhere to the Random Utility Model and the choice modeling literature by McFadden (2001), Hole (2007), and Train (2009), the latter who follows the binomial logit model (e.g., Ben-Akiva and Lerman 1985). Eq. (1) gives the utility U_{njt} of individual *n* when choosing choice alternative *j* in choice scenario *t*. Respondents choose the choice alternative j for which U_{njt} is largest, determined by the systematic utility V_{njt} and the random disturbance term ε_{njt}.

$$U_{njt} = V_{njt} + \varepsilon_{njt} . \tag{1}$$

The systematic utility V_{njt} is a function of the attributes of alternative j (eq. (3)). The random disturbance term ε_{njt} includes a variety of unobserved effects such as unknown characteristics and disregarded attributes, measurement errors, and heterogeneity of tastes. The probability P_{nit} in eq. (2) describes the probability that the utility of individual *n* is higher when selecting choice alternative *i* rather than *j*.

$$P_{nit} = P(U_{nit} > U_{njt}) = P(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt}) = P\big(\varepsilon_{njt} - \varepsilon_{nit} < V_{nit} - V_{njt}\big). \tag{2}$$

The systematic utility V_{njt} is a function of the attributes of choice alternative *j* and specified to be linear in the alternative attributes, as depicted in eq. (3):

$$V_{njt} = \beta_{0i} + \beta_1 X_{1njt} + \cdots + \beta_K X_{Knjt} + \beta_C C_{njt} , \tag{3}$$

where the constant β_{0i} is the mean of the unobserved effects on the utility of choice alternative i and $\beta_1, \dots, \beta_K$ are the coefficients for attributes $X_1, \dots, X_K$; β_C is the coefficient for the cost C_{njt} of the choice alternative *j*.

In case the individual-specific and time-invariant unknown effects correlate with the alternative attributes, Hole (2007) advises to use the fixed effects logit model by Chamberlain (1980). Thus, we make use of the repetitiveness of choices and use conditional logit models, including fixed effects at the participant level, as suggested by Chamberlain (1980) and Greene (2003).[2] In that case, $i = 1,2, \dots, n$ denotes the independent groups and $t = 1,2, \dots, T_i$ denotes the observations for the *i*th group. The observed choice of group i in observation t is denoted by the dependent variable y_{it} and equals 0 or 1. The outcomes for the *i*th group as a whole is $y_i = \big(y_{i1}, \dots, y_{iT_i}\big)$ and x_{it} is a row vector of covariates. Then the observed number of ones for the dependent variable in the *i*th group takes the form:

$$k_{1i} = \textstyle\sum_{t=1}^{T_i} y_{it}. \tag{4}$$

The conditional probability for a possible value of y_{it} conditional that $\sum_{t=1}^{T_i} y_{it} = k_{1i}$ is given by:

[2] We also applied a mixed logit model for panel data per Revelt and Train (1998). The results are very similar to the conditional (fixed-effects) logistic model, and available from the authors upon request.

$$P\left(y_{it}\middle|\sum_{t=1}^{T_i} y_{it} = k_{1i}\right) = \frac{\exp\left(\sum_{t=1}^{T_i} y_{it}x_{it}\beta\right)}{\sum_{d_i \in S_i} exp\left(\sum_{t=1}^{T_i} d_{it}x_{it}\beta\right)}\,, \tag{5}$$

where d_{it} takes on the values 0 or 1, the sum equals to k_{1i} ($\sum_{t=1}^{T_i} d_{it} = k_{1i}$) and S_i is the set of all possible combinations of k_{1i} ones and k_{1i} zeros. The fixed-effects conditional logit model is given by:

$$P(y_{it} = 1|x_{it}) = F(\alpha_i + x_{it}\beta)\,, \tag{6}$$

where F is the cumulative logistic distribution given in eq. (7):

$$F(z) = \frac{\exp(z)}{1+\exp(z)}\,. \tag{7}$$

To analyze the interaction between the continuous variable *charging spots* and the categorical attribute levels, we employ a full factorial interaction design where the estimation provides us with two coefficients for each variable, one for the main effect (e.g. *8 h charging duration*) and another one for the interaction effect (e.g. *8 h duration ∗ charging spots*).

Hole (2007) calculates the monetary value that respondents are willing to pay, WTP_k, for improving attribute X_k by taking the total derivative of eq. (1) with respect to changes in attribute X_k and cost C. Thus, from eq. (1) we derive $\mathrm{d}U_{njt} = \beta_k \mathrm{d}X_k + \beta_C \mathrm{d}C$, set it equal to 0, and solve for $\frac{\mathrm{d}C}{\mathrm{d}X_k}$, yielding:

$$\frac{\mathrm{d}C}{\mathrm{d}X_k} = WTP_k = -\frac{\beta_k}{\beta_c}. \tag{8}$$

Eq. (8) is the negative of the ratio of the attribute coefficients β_k and the cost coefficient β_c. For calculating the WTP in terms of unit changes – 1 minute less in charging duration is worth X Euros – we specify an additional estimation with numeric variables, except for technology and location which we always compare to their base levels. Since we also specify this numeric estimation in a full factorial design, we again obtain two coefficients for each variable, i.e. the main effect (e.g. *charging duration*) and the interaction effect (e.g. *charging duration ∗ charging spots*). To account for not only the main effects (ME) but also for the interaction effects (IE) in terms of one charging spot, we modify eq. (8) to eq. (9), which is the amount $WTP_{k,ME+IE,CS}$ respondents are willing to pay for improving attribute X_k subject to the offer of charging spots CS. In the nominator of eq. (9), we add the main effect coefficients $\beta_{k,ME}$ and the interaction coefficients $\beta_{k,IE}$ which is multiplied by the number of charging spots $CS = 0, 1, \ldots, I$. We do the same for the cost coefficients β_c in the denominator so that we end up with four coefficients and CS.

$$WTP_{k,ME+IE,CS} = -\frac{\beta_{k,ME} + \beta_{k,IE} \cdot CS}{\beta_{c,ME} + \beta_{c,IE} \cdot CS} \tag{9}$$

Eq. (9) is the negative of the ratio of the full factorial attribute coefficients β_k and the full factorial cost coefficients β_c where the IE coefficients are multiplied by the number of charging spots CS. For $CS = 0$, eq. (9) calculates the WTP with the two main effect coefficients per attribute only and hence this *main effect WTP* represents a monetary valuation where there are no charging spots available. For $CS = 1$, eq. (9) gives the *full factorial WTP* where there is one charging spots available. For calculating the WTP for other quantities, we multiply the coefficients by the designated number of charging spots.

In doing so, we can estimate the effect of different factors on choice probabilities – always subject to the number of charging spots – and narrow down the WTP for different features of the EV charging infrastructure and further preferences for EV charging.

3. The Data

3.1 Descriptive DCE Statistics

The data sample (N = 4,101) consists of drivers' license holders only and is restricted to ≤ 75 years *ex ante*. 97% are car owners of which most own 1 or 2 gasoline or diesel cars. 4% of the respondents own hybrid cars and 2% own EVs (N = 84). 72.40% have a private parking spot at home and thus could possibly charge at home, provided the installation is done (German average 73%, German Mobility Panel 2019). The average daily car commute amounts to 36.86 km, which corresponds to the German average commuting distance (German Mobility Panel 2019; own calculations) as well as to EV literature with a focus on Germany (Franke and Krems 2013). The sample represents the German population also with respect to the spatial dispersion of participants. With an *ex ante* self-stated knowledge on EVs in general, we reached a share of 50% *EV experts* in our sample, e.g. EV owners, respondents who have driven an EV before or think about buying one within the next 3-5 years.[3] Later, we use this categorization for differentiating the consumer group *EV experts*. The range of the EV, dynamic pricing (e.g. a discount for night charging), compatibility of charging points of different providers, and the possibility to reserve a charging spot were also considered as important for the charging decision, which corroborates the findings in Wolbertus et al. (2018b) and Latinopoulos et al. (2017), respectively, and has led us to the idea to combine the DCE data set with available public charging spot offers.

[3] The screening questions used for the self-stated knowledge were: (1) Have you ever driven an EV or a hybrid car (for a test drive, with friends or family, or using car-sharing services? (2) Which drivetrain technology would you buy in the next 3 years? (3) On a scale from 1-5, how do you assess your knowledge about electric mobility?

3.2 Matching the Data Sets

We matched the DCE sample with the data set of public charging spots as described in section 2.2. The match consists of 4,101 respondents living in 1,712 consolidated zip code areas with no or at least one of 10,727 publicly accessible charging spots in total. 11% of the respondents (N = 461) live in those 22% of the areas (N = 375) with no charging spots (Figure 2).

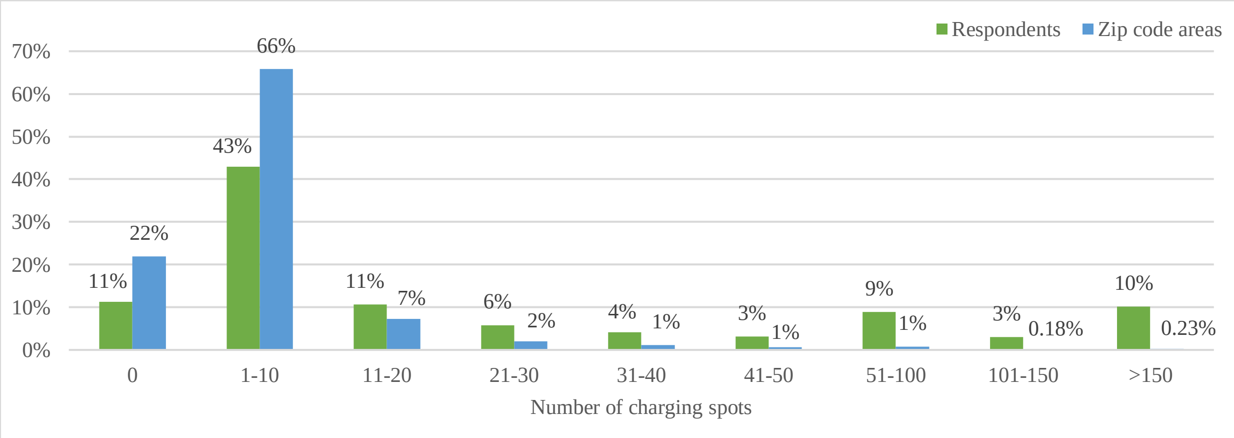

Figure 2: Allocation of charging spots in the sample with respect to number of respondents and zip code areas

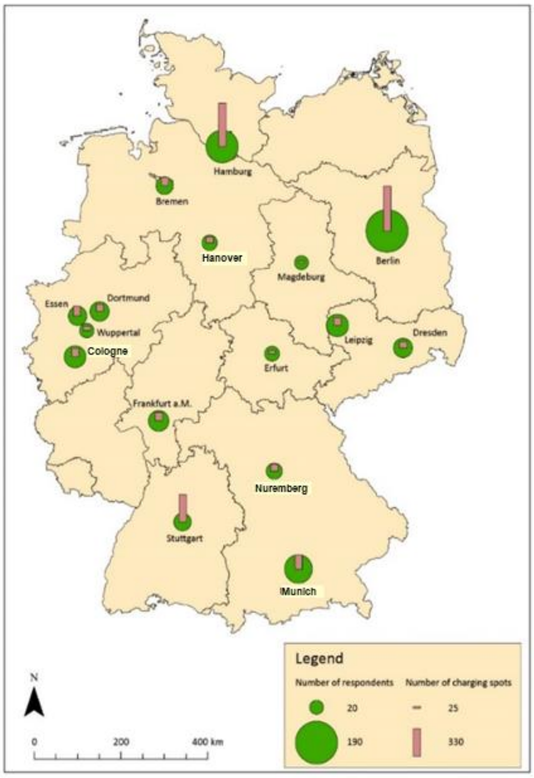

Figure 3: Allocation of charging spots and respondents across Germany (as of October 2019).

Apart from areas with 0 charging spots, most zip code areas in the data set have either 1 or 2 charging spots (303 and 234 areas, respectively) and cover villages or smaller towns. Overall, most respondents (53%) as well as most areas (66%) have 1-10 charging spots. As can be seen in Figure 3, according to our data four German cities exhibit the highest quantity of charging spots in the sample: Berlin (530), followed by Hamburg (511), Stuttgart (327), and Munich (169 charging spots) with in total 416 respondents.[4]

3.3 Discrete Choice Models

We interact the DCE attributes with the 10,732 public charging spots using a conditional logit model (Table 3, Figure 4-Figure 6) and subsequently derive the WTP for each attribute when interacting with the number of charging spots in the area concerned (Table 4-Table 6).

For the full factorial interaction of the categorical DCE variables (i.e. the attribute level coefficients), the main effect for each variable is statistically significant, including the effect for the continuous variable *charging spots*). However, the interaction effects are statistically significant for only two attribute levels interacting with *charging spots*: *8 h charging duration* compared to the base case of *10 min charging duration* as well as *75% RES* compared to the base case of *25% RES* interacting with *charging spots* (McFadden's Pseudo R^2 = 0.22). We apply the same procedure to the subsample *EV experts* for which only the interaction of *€200* compared to *€50 charging costs* with *charging spots* is statistically significant (McFadden's Pseudo R^2 = 0.21). We confirm the statistical significance of these interactions by Wald Tests.

Since the participants trade off their choice options, we interpret the marginal effects of the estimation in terms of tradeoffs, i.e. always in relation to some base case. The average marginal effects per charging spot shown in Table 3 are graphically represented in Figure 4, where the orientation of the bars mirrors negative or positive effects and the color of the bars reflects the size of the effects.

In descending order of the effect sizes, the DCE participants prefer – on average – charging at the lowest costs, shorter durations, at home to at work to roadside charging, higher shares of renewables, shorter waiting times, and inductive to cable charging. EV experts exhibit an analogous preference order, yet, the magnitudes vary slightly, especially when corrected for standard errors. EV experts prefer slightly longer charging durations and higher RES shares than the full sample because the marginal effects are higher than for the full sample. EV experts put less emphasis on lower costs than the full sample (marginal effects are smaller).

[4] The quantities of charging spots per consolidated zip code area vary, depending on the data source used and the definition of public charging (see also section 2.2).

Table 3: Average marginal effects per average number of charging spots

Attribute/Variable	Attribute level	Full sample (N = 4,101)	EV experts (N = 2,051)
Number of charging spots	1	-0.29*** (0.81)	-0.33*** (0.10)
Charging location	At home	(base case)	(base case)
	On the road (main goal)	-7.05*** (0.62)	-6.98*** (0.94)
	On the road (side activity)	-5.87*** (1.02)	-5.72*** (0.89)
	At work	-4.15*** (1.35)	-3.57*** (0.84)
Charging duration [min, h]	10 min	(base case)	(base case)
	30 min	-1.16*** (0.25)	-1.37*** (0.36)
	4 h	-5.98*** (0.45)	-6.22*** (0.58)
	8 h	-9.46*** (0.67)	-9.69*** (0.84)
Technology	Tethered (cable charging)	(base case)	(base case)
	Inductive	1.10*** (0.15)	1.33*** (0.21)
Waiting time [min]	0	(base case)	(base case)
	5	0.04 (0.47)	-0.38 (0.68)
	10	-0.46 (0.47)	-0.61 (0.68)
	30	-2.60*** (0.49)	-2.58*** (0.69)
Renewable share [%]	25	(base case)	(base case)
	50	1.70*** (0.24)	2.07*** (0.34)
	75	2.61*** (0.29)	3.02*** (0.40)
	100	4.06*** (0.37)	4.68*** (0.51)
Total charging cost [€/month]	50	(base case)	(base case)
	100	-8.57*** (0.62)	-8.10*** (0.73)
	150	-14.65*** (1.02)	-13.72*** (1.16)
	200	-19.10*** (1.35)	-18.24*** (1.54)

Note: Effect in %. Standard errors in parentheses. Significant at the *p<0.05, **p<0.01, and ***p<0.001 level. Full sample (N = 4,101): McFadden's Pseudo R^2 = 0.22; EV experts (N = 2,051): McFadden's Pseudo R^2 = 0.21.

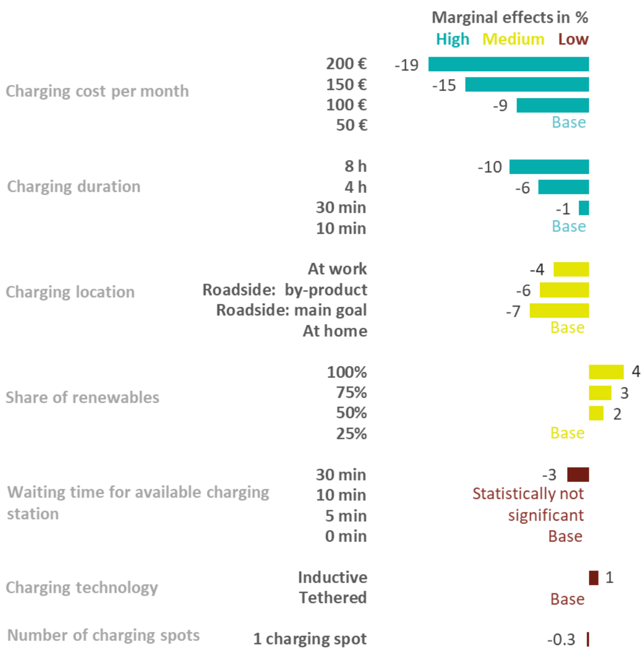

Figure 4: Average marginal effects per average number of charging spots (full sample), in % (high, medium, low)

The estimation bases the interaction on average values. Therefore, Table 3 and Figure 4 show the average marginal effects of the interaction of the choice models with the continuous interaction variable *charging spots* at its average (μ = 62 charging spots). However, we aim at refining our analysis to the effect of one additional charging spot on choice behavior. To this end, we estimate the effects of the attribute levels at 0, 1, 2, …, 530 charging spots instead of at the average, and now turn towards predictive margins (also termed predicted probabilities) to also graphically interpret results in terms of positive probabilities, instead of in terms of mostly negative marginal effects compared to some base case.

Figure 5(a) shows the full sample's predictive margins and confidence intervals across all six attributes (i.e. at the average of all the attributes) at the exactly 0 to 530 charging spots (i.e. not at the average of the variable *charging spots*). With growing numbers of charging spots, the curve slopes downward until it asymptotically approaches the x-axis. The higher the charging point quantities are, the lower are the predictive margins. Also, the curve slopes downward at a lower rate with rising charging spot quantities, so that we observe diminishing predictive margins. This diminishing decline reveals that the non-availability of public charging spots has a larger effect on the choice probability than 1, 2, or 3 charging spots have. Respondents become more and more indifferent the more charging spots there are, e.g. the awareness of 0 or 1 charging spot/s is higher than for 1 or 2 charging spot/s. Consequently, respondents' choices depend on the quantity of charging spots available in the area they live in.

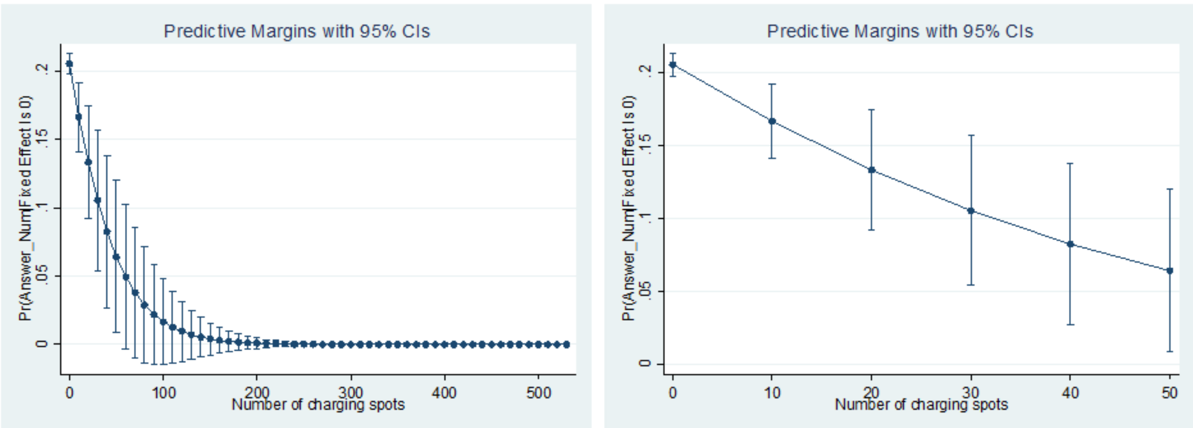

Figure 5: (a) Full sample's predictive margins and confidence intervals from 0 to 530 charging spots (left) and (b) from 0 to 50 charging spots (right)

The confidence intervals in Figure 5(a) grow from 0 to 50 charging spots and then shrink from 60 charging spots onward. Wider confidence intervals suggest more variation in the data. In Figure 5(a) we also see that from 60 charging spots onward, the lower confidence bounds become negative. The p-values < 0.05 confirm our suspicion: only the predictive margins up until 50 charging spots are statistically significant.[5] In Figure 5(b), we therefore plot the predictive margins at 0, 10, …, 50 charging spots. We limit the further analysis to 50 charging spots by simultaneously keeping the original sample size. This procedure uncovers statistically significant interactions hidden in the marginal effects at the average of the variable *charging spots*.

For each of the six attributes, Figure 6 shows the full sample's predictive margins and confidence intervals from 0 to 50 charging spots.[6] Analogously to the predictive margin across all attributes in Figure 5, all curves slope downward, and they do so at a lower rate with rising charging spot quantities, so that we observe diminishing predictive margins. Interestingly, some curves (representing the different attribute levels) within attributes almost converge. Thus, for all six attributes and their levels it holds that with rising charging spot quantities, predictive margins become smaller and the gaps between attribute levels also become smaller. Again, an increase from 0 to 1 charging spot/s has a higher impact on choice behavior than an increase from 1 to 2 charging spots.

Charging location (top left in Figure 6): *Ceteris paribus*, participants with 0 charging spots are most likely to prefer charging at home (27%) over at work (21%) over roadside charging (17-18%), with all figures rounded. Of those participants with 50 charging spots, 9% favor at-home charging, 7% at-work charging, and around 5-6% roadside charging. The difference between the four locations (i.e. attribute levels) diminish as the curves converge. Thus, the key finding is that among the four attribute levels, the charging location becomes less significant the more charging spots are publicly available. The confidence intervals grow with growing numbers of charging spots and are bigger for at-home and at-work charging than for roadside charging, i.e. there is more variance inherent in these attribute levels. On average, location has a medium-sized effect on choice behavior as the marginal effects between 4-7% in Figure 4 highlight.

Charging duration (top right): Overall, shorter durations are preferred. Again, holding all other attributes constant, participants with 0 charging spots select 10 min, 30 min, 4 h, and 8 h on average by 27%, 25%, 18%, and 13%, respectively. At 20 charging spots, these preferences drop to on average 18%, 16%, 11%, and 8%, and at 50 charging spots to 9%, 8%, 5%, and 4%. These drops reveal that with every additional charging spot, the charging duration becomes less important in the choice behavior. Confidence intervals expand with a growing number of charging spots. The difference between 10 min and 30 min appears smaller than between 4 h and 8 h, yet the (graphical) representation is biased since the difference between them is only 20 min compared to a 4-hour difference between 8

[5] One reason could be the missing variation in the charging spot frequencies from 50 spots onwards. Even though the sample size is substantial (there are 188 participants from Berlin with 530 charging spots and 110 participants from Hamburg with 511 charging spots), there is no observation with e.g. 500 charging spots. From 0-50 charging spots, however, there is an almost seamless series of charging spots.

[6] For reasons of simplicity and clarity, we refrain from presenting six tables listing the predictive margins illustrated in Figure 6. Additional tables can be obtained from the authors upon request.

h and 4 h. Still, it shows that the participants value 10 min and 30 min almost equally. Duration is the second-most important attribute, as shown by the large marginal effect of up to 10% in Figure 4.

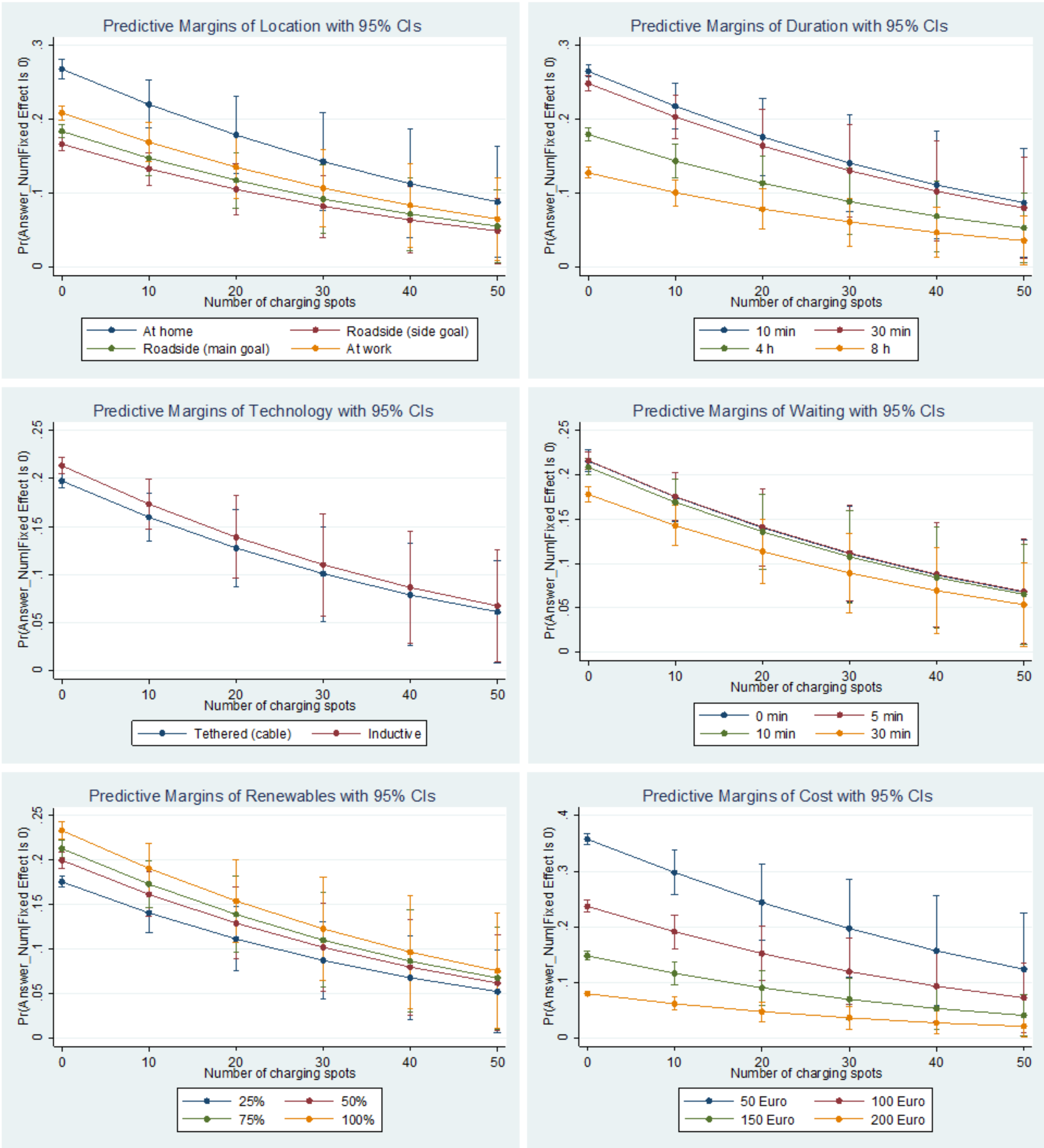

Figure 6: Full sample's predictive margins and confidence intervals for the six attributes, from 0 to 50 charging spots

Charging technology (middle left): While not yet common practice, respondents slightly prefer inductive over cable charging by around 1 percentage point, *ceteris paribus*. This diminutive distinction is also indicated by the smallest marginal effect of 1% in Figure 4. At 0 charging spots, respondents favor inductive charging by 21%, whereas 20% of the respondents prefer cable charging. Likewise, at

50 charging spots, respondents favor inductive charging by 7%, whereas 6% of respondents prefer cable charging. The confidence intervals broaden with more charging spots available/in situ.

Waiting time (middle right): Overall, shorter waiting times are preferred. With no charging spots on site, 0 min and 5 min are preferred by 22%, 10 min by 21%, and 30 min by 18% of the respondents. Note that in the experiment waiting time is always fixed to 0 min for home charging. At 50 charging spots, the preferences decrease to 7% for both 0 min and 10 min, and to 5% for 30 min. Again, confidence intervals expand with growing charging spot availability. As indicated in Table 3 and Figure 4, the average marginal effects of the interaction of 5 and 10 min with charging spots are the only two average marginal effects that are not statistically significant, whereas all the predictive margins at 0-50 charging points shown in Figure 6 are statistically significant.

Share of renewables (bottom left): Higher renewable energy shares (RES) are preferred. Yet, the overall preference levels decrease with growing charging spot availability. Recall that, in the estimation, only the coefficient of *75% RES* interacting with *charging spots* compared to the base case of *25% RES* was statistically significant. Yet, all RES predictive margins at 0-50 charging spots are statistically significant. Participants with 0 charging spots opt for 25%, 50%, 75%, and 100% RES in 18%, 20%, 21%, and 23% of the cases, respectively. The differences between the four levels diminishes with rising charging spot quantities, so that participants with 50 charging spots pick them in 5%, 6%, 7%, and 8% of the cases, respectively.

Charging costs (bottom right): The overall results are intuitive: lower costs are preferred. Holding all other attributes constant, a participant with 0 charging spots prefers €50 in 36%, €100 in 24%, €150 in 15%, and €200 in 8% of the cases. A participant with 50 charging spots prefers them in 12%, 7%, 4%, and 2% of the cases, respectively. The confidence intervals are very small for the highest costs of €200. Thus, there is less variation in choice behavior when dealing with €200. Most of the time, respondents decide against €200 and for the cheaper option. On the other hand, €50 have the widest confidence intervals. Extensive confidence intervals for €50 suggest extensive variation in the data, i.e. often respondents opt against the cheapest option in turn for better non-cost attribute levels. Costs are by far the most important factor because we observe the largest predictive margins and the largest differences between the attribute levels, as also depicted by the largest marginal effect of up to 19% in Figure 4.

3.4 Willingness to Pay

Table 4 shows the *main effect WTP* according to eq. (9) for $CS = 0$, i.e. only the main effects are taken into account so that this specific WTP represents a monetary valuation as if there were no charging spots available in the area. However, the full estimation still includes the interaction coefficients. The upper and lower bounds reveal the confidence intervals.

Table 5 (full sample) and Table 6 (EV experts) show the *full factorial WTP* for $CS = 1, \dots, 530$. Hence, this specific WTP adds up the main effects and the interaction effects assuming one charging spot. The first columns in Table 5 and Table 6, respectively, show the average WTP for $CS = 0, \dots, 530$. The second columns repeat the values for 0 charging spots from Table 4. The third columns show the WTP when there is only 1 charging spot on site. From the fourth columns onwards, we list the WTP when attributes interact with 50, 100, 150, 200, or 250 charging spots.

Most importantly, the WTP analogously reveals those interactions reflected by the predictive margins and the average marginal effects considered previously: the WTP varies with increasing number of charging spots.

Charging spots: The first line in Table 4 gives the WTP for one additional charging spot in town: respondents are willing to pay – on average – 2.20 €/month within a substantial range of almost €3 (0.71-3.68 €/month). EV experts would pay around €0.50 more so that they are willing to pay – on average – 2.69 €/month with bounds of €2 lower or higher (0.68-4.69 €/month).

Charging duration: At 0 charging spots, respondents are willing to pay an extra 0.16 €/month (full sample) or 0.17 €/month (EV experts) for a reduction of 1 min in charging time. In Table 4, these WTP oscillates between 0.15-0.17 €/min and 0.16-0.18 €/min per month, respectively. From 150 charging spots onwards, the full sample's initial motivation to pay 0.16 €/month for a 1-min reduction in charging duration reduces fractionally to 0.15 €/month (Table 5). EV experts tend to pay slightly more and are indifferent towards the charging spot abundance, so that the WTP remains constant at 0.17 €/month even with additional charging spots (Table 6).

Waiting time: At 0 charging spots, respondents are willing to pay as much as 0.82 €/month (full sample) and 0.75 €/month (EV experts) for a reduction of 1 min in waiting time, which varies between 0.70-0.94 €/min and 0.57-0.92 €/min per month, respectively. Participants assign higher preference (i.e. here monetary valuation) on a reduction in waiting time than on a reduction in charging time. From 0-250 charging spots, the full sample's WTP declines minimally from 0.82 €/month to 0.81 €/month, whereas the EV experts' WTP increases vastly by €0.18 from 0.75 €/month to 0.93 €/month. While the full sample's WTP for a 1-min reduction in waiting time decreases with increasing charging spot quantities, the EV experts' WTP increases.

Share of renewables: Participants value an additional 1% RES with 0.40 €/month (full sample, range: 0.36-0.44 €/month) and 0.49 €/month (EV experts, range: 0.43-0.55 €/month). The marginal propensity to pay for 1% more green electricity rises with rising amounts of charging spots — from 0.40 €/month to 0.48 €/month for the full sample and from 0.49 €/month to 0.54 €/month for EV experts.

Technology: For charging inductively instead of connecting a cable, participants would pay 8.48 €/month (6.54-10.42 €/month). In contrast, EV experts would pay a €2-surcharge, so that their WTP amounts to 10.84 €/month (7.96-13.73 €/month) for charging inductively. From 0-250 charging spots the WTP for induction rather than cable charging drops by €0.45 from 8.48 €/month to 8.03 €/month. From 0-530 charging spots, the WTP drops by €1.

Table 4: Willingness to pay subject to the number of charging spots $CS = 0$ (full sample, EV experts)

Variable	Full sample WTP for $CS = 0$	Full sample Lower bound	Full sample Upper bound	EV experts WTP for $CS = 0$	EV experts Lower bound	EV experts Upper bound
Charging spot	2.20	0.71	3.68	2.69	0.68	4.69
Charging duration (reduction by 1 min)	0.16	0.15	0.17	0.17	0.16	0.18
Waiting time (reduction by 1 min)	0.82	0.70	0.94	0.75	0.57	0.92
Renewable share (increase by 1%)	0.40	0.36	0.44	0.49	0.43	0.55
Technology (inductive instead of cable)	8.48	6.54	10.42	10.84	7.96	13.73
Charging location:						
At home	(base)	(base)	(base)	(base)	(base)	(base)
On the road (main goal)	-48.20	-51.95	-44.44	-53.90	-59.50	-48.30
On the road (side activity)	-38.11	-41.83	-34.39	-42.39	-47.94	-36.84
At work	-24.47	-28.16	-20.77	-24.68	-30.18	-19.18

Note: WTP in €/month. Full sample: McFadden Pseudo R^2 = 0.22, N = 4,101. EV Experts: McFadden Pseudo R^2 = 0.21, N = 2,051.

Table 5: Willingness to pay (full sample)

Variable	Average WTP for $CS = 0, \ldots, 530$	WTP subject to the number of charging spots CS: 0	1	50	100	150	200	250
Charging duration (reduction by 1 min) ∗ charging spots	0.16	0.16	~	~	~	0.15	~	~
Waiting time (reduction by 1 min) ∗ charging spots	0.82	0.82	~	~	~	0.81	~	~
Renewable share (increase by 1%) ∗ charging spots	0.42	0.40	0.40	0.42	0.43	0.45	0.47	0.48
Technology (inductive instead of cable) ∗ charging spots	8.37	8.48	8.48	8.39	8.30	8.21	8.12	8.03
Charging location:								
At home	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)
On the road (main goal) ∗ charging spots	-46.18	-48.20	-48.16	-46.64	-45.07	-43.48	-41.88	-40.26
On the road (side activity) ∗ charging spots	-35.62	-38.11	-38.06	-36.18	-34.24	-32.28	-30.30	-28.29
At work ∗ charging spots	-22.22	-24.47	-24.44	-22.73	-20.92	-19.17	-17.36	-15.44

Note: WTP in €/month.

Table 6: Willingness to pay (EV experts)

Variable	Average WTP for $CS = 0, \ldots, 530$	WTP subject to the number of charging spots CS: 0	1	50	100	150	200	250
Charging duration (reduction by 1 min) ∗ charging spots	0.17	0.17	~	~	~	~	~	~
Waiting time (reduction by 1 min) ∗ charging spots	0.80	0.75	0.75	0.78	0.82	0.85	0.89	0.93
Renewable share (increase by 1%) ∗ charging spots	0.50	0.49	0.49	0.50	0.51	0.52	0.53	0.54
Technology (inductive instead of cable) ∗ charging spots	10.23	10.84	10.85	10.41	9.95	9.48	8.99	8.48
Charging location:								
At home	(base)	(base)	(base)	(base)	(base)	(base)	(base)	(base)
On the road (main goal) ∗ charging spots	-50.53	-53.90	-53.84	-51.50	-49.04	-46.50	-43.87	-41.15
On the road (side activity) ∗ charging spots	-39.30	-42.39	-42.34	-40.19	-37.93	-35.60	-33.18	-30.68
At work ∗ charging spots	-21.89	-24.68	-24.73	-22.73	-20.62	-18.44	-16.18	-13.85

Note: WTP in €/month.

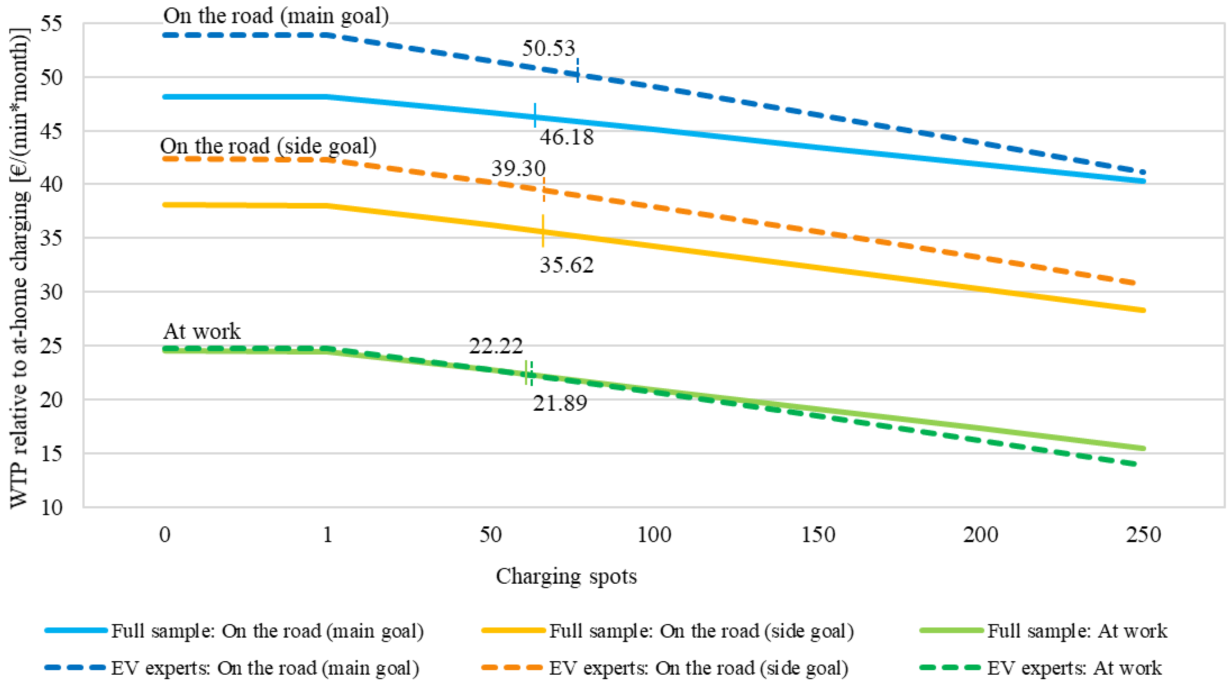

Figure 7: WTP of charging at home instead of indicated location when location is interacting with the number of charging spots and intersections with average WTP (full sample, EV experts)

Location: With no charging spots available, participants would pay as much as 48.20 €/month for charging at home and not primarily on the road as a main goal (Table 4, range 44.44-51.95 €/month, spread €7.51). EV experts are willing to pay an additional €5.70, i.e. 53.90 €/month, and they would pay up to around €60 (48.30-59.50 €/month, spread €11.20). With a spread of €11.20, this group exhibits the widest confidence intervals. Hence, there are individuals who would pay around €11 more or less for not charging on the road (as a main goal). Roadside charging as a side activity remains equally unpopular, so that the full sample would pay 38.11 €/month (34.39-41.83 €/month, spread €7.44) and the EV experts 42.39 €/month (36.84-47.94 €/month, spread €11.10). Besides home charging, at-work charging is the second-best (i.e. second-most preferred) location, hence, the tradeoff between them is made by the values of 24.47 €/month (20.77-28.16 €/month, spread €7.39) and for EV experts by 24.68 €/month (19.18-30.18 €/month, spread exactly €11). Both groups exhibit the largest confidence intervals in the location choice, exhibiting a considerate variation in choice behavior.

Anticipating the WTP for location in Table 5 and Table 6, the more charging spots there are in the area, the lower is the WTP for at-home charging than charging anywhere else. With only 1 charging spot, the full sample is willing to pay on average 48.16 €/month for charging at home instead of on the road (main goal), which decreases by €7.90 to 40.26 €/month for 250 charging spots. With charging spot quantities growing from 1 to 250, the WTP for charging at home rather than on the road (side activity) decreases by almost €10 from 38.06 €/month to 28.29 €/month, whereas the WTP for charging at home instead of at work decreases by exactly €9 from 24.44 €/month to 15.44 €/month. On average, the full sample is willing to pay around 22 €/month more for charging at home rather than at work and around 36-46 €/month more for charging at home rather than on the roadside (both main and side activity).

Analogously, EV experts are willing to pay 53.84 €/month for charging at home rather than on the road (main goal) with only 1 charging spot in the area. For 250 charging spots, this WTP decreases by around €12 to 41.15 €/month. The WTP for charging at home instead of on the road (side activity) also decreases by around €12 from 42.34 €/month to 30.68 €/month. The WTP for charging at home instead of at work decreases by around €11 from 24.73 €/month to 13.85 €/month.

Eventually, EV experts become indifferent. 515 charging spots mark the tipping point at which EV experts are indifferent between at-home and at-work charging. When the tipping point is exceeded from 516 charging spots onwards, EV experts rather charge at work than at home. Thus, with increasing numbers of charging spots, public charging spots in the home neighborhood are less relevant than those near work. For example, with 530 charging spots on site, for 0.88 €/month EV experts rather charge at work than at home.

On average, EV experts are willing to pay around 22 €/month more for charging at home rather than at work and around 40-51 €/month more for charging at home rather than on the roadside (both main and side activity).

To sum up the WTP obtained by location, we observe significant numerical divergences between the full sample and EV experts. Figure 7 illustrates these heterogeneities in the WTP by type of location of the full sample and the subsample EV experts, where we also give the intersections with the average WTP for $CS = 0, \ldots, 530$ from the first columns in Table 5 and Table 6.

Most importantly, Figure 7 illustrates that EV experts' WTP for at-home charging instead of on the road slopes downward steeper (dark colors) than the WTP of the full sample (light colors). For charging on the road (both main and side activity), every additional charging spot has a stronger effect on EV experts than on the full sample. As the number of charging spots increases, the two curves converge, though. For example, for charging at home instead of at work, WTP is almost equal for 0-100 charging spots but diverges for charging spot quantities >100. Analogously to the predictive margins, the changes in WTP reveal that among the four attribute levels, the charging location becomes less significant the more charging spots are becoming publicly available. Further, EV experts seem to be more perceptive of charging spots available to them. This appears to be reasonable in light of the EV experts' expected higher perception of charging spot availability.

Table 4-Table 6 exhibit the WTP for the time attributes duration and waiting time as average values across all four attribute levels. In Figure 8 and Figure 9, we divide the WTP into the original time intervals. For charging duration, we see a significant difference between the monetary valuation of WTP for specific time intervals relative to the number of charging spots. Note that in Figure 9, the WTP for 0 min is negative because in the experiment waiting time is always fixed to 0 min for home charging. Apart from that, the WTP for reducing the waiting time is around five times larger than for accelerating the charging speed.

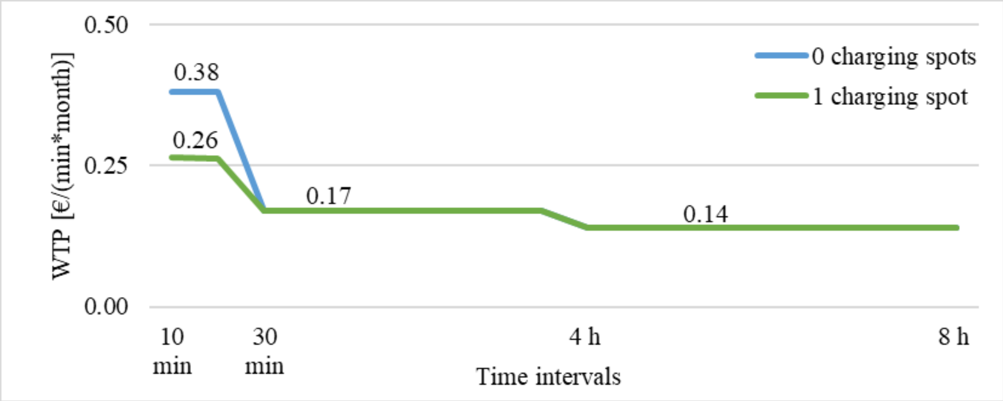

*Figure 8: Change in WTP for lower charging duration at specific time intervals (full sample, in €/(min*month))*

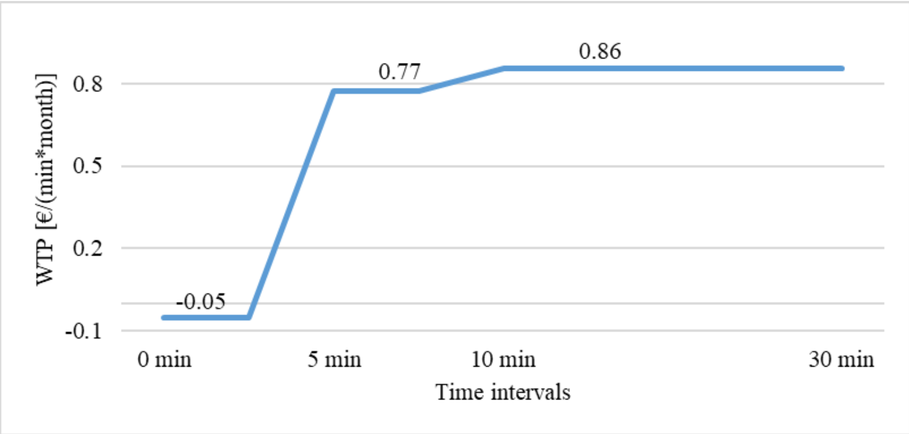

Figure 9: Change in WTP for lower waiting times at specific time intervals subject to the number of charging spots $CS = 0$ *(full sample, in €/(min*month))*

4. Discussion

We discuss the results in terms of (average) marginal effects, predictive margins, and WTP. While we calculate the WTP from the estimation coefficients with a numeric variable specification (eq. (9)), it analogously reveals those interactions reflected by the predictive margins as well as by the average marginal effects: the WTP varies with increasing number of charging spots. Numerically, the descending order of the effect sizes in Table 3 are equivalent to those calculated in Wolff and Madlener (2019), however, adjusted by the charging spot interaction terms. The adjustment factors for charging spot interaction reduce the marginal effects by a magnitude of 9 percentage points for cost of €200 to 1 percentage points for e.g. a 25% share of RES. This means that the interaction not only changes the effect size but also the relation between the attribute levels.

Respondents' choices depend on the quantity of charging spots. Thus, they are somewhat aware of charging spot quantities locally available to them. We show that an increase from 0 to 1 charging spot/s has a higher impact on choice behavior than an increase from 1 to 2 charging spot/s. Respondents become more and more indifferent between the attribute levels the more charging spots there are. This could serve as a further evidence of charging point awareness with the awareness of 0 or 1 charging spot/s being higher than for 1 or 2 charging spot/s.

4.1 Charging Location

Looking at spatial heterogeneity, the most intriguing part of this study is the *ceteris paribus* interaction of charging location with the number of charging spots. Overall, charging at home and at work are more relevant to the participants. On average, both the full sample as well as EV experts are willing to pay around 22 €/month more for charging at home rather than at work, and around 36-46 €/month (EV experts: 40-51 €/month) more for charging at home rather than on the roadside (both main and side activity).

Figure 4, Figure 6, and especially Figure 7 illustrate the preference gap between at-home charging and the other three locations. With rising charging spot quantities, this gap becomes smaller while the confidence intervals expand. Still, charging at home and at work remain more relevant than roadside charging even with increasing numbers of charging spots. In contrast, the shrinking gap also means that while there are more charging spots, the less often participants want to charge at home rather than anywhere else. This is also reflected by the drop in the WTP across all locations, i.e. the WTP for charging at home decreases the more charging spots there are. Consequently, charging anywhere else than at home becomes more reasonable for respondents when there is more than 1 charging spot available in the area. In a similar choice study, with charging location depending on the range of the EVs, Chakraborty et al. (2019) also obtain at-home and at-work charging as the most requested charging locations

An increase in charging spot availability increases respondents' willingness to charge away from home, also among non-EV owners, up to 515 charging spots, where they are indifferent between at-home and at-work charging. Still, charging at home remains important but with substantial variations in the choice behavior. Both the full sample and EV experts exhibit the largest confidence intervals in the WTP for location; hence, there is a considerable variation in choice behavior regarding location. In contrast to costs sensitivity, where respondents clearly disapprove the highest cost, respondents seem to choose indistinctively between the four locations even though location is the third-most important attribute. Hence, there are individuals who would pay either more or less than the average for charging at the preferred location. Also, for at home vs. on the road charging (main goal), we observe the largest differences in WTP between full sample and the subsample EV experts (5.70 €/month).

This bifurcates the discussion. On the one hand, the dominance of at-home charging raises the question whether public charging infrastructure (far from residential areas) should be of the highest priority, whereas at-work charging in non-residential areas should also not be neglected. On the other hand, the more charging spots there are, the less is the demand for home charging. Respondents somewhat rely on the thought that they will find a charging possibility outside their homes. However, this evidence could be biased by the fact that the more charging spots there are, the larger is the population size in that area. Also, technophilia could play a role here: urban population tends to be more open to technical solutions (outside their homes), and they are used to and rely more often on sharing offers such as car and bicycle sharing services. Also, this evidence could be biased by the fact that the more charging spots there are, the less often participants want to charge at work or on the roadside.

This twofold discussion is interesting from a policy perspective because it suggests a need for more charging spots at home (residential areas) or at work (mixed-use and non-residential areas). This might enhance EV sales/ EV usage. There could be empirical evidence to increase purchase intention. Also, the booking of charging spots in advance would enhance the reliability on finding a public charging spot away from home. The charging location is closely linked to the waiting time because it highly depends on where users have to spend time in order to recharge. We will continue the spatial-temporal aspect in section 4.4 on waiting time. Then it is interesting to see whether the installation of additional charging spots pays off through a higher WTP for charging at the preferred location.

4.2 Charging Duration

Regarding the duration, the participants are indifferent towards the charging spot abundance. While the number of charging spots steadily increases from 0-250 (Table 5 and Table 6), the WTP for a 1-min reduction in charging time varies only slightly between 0.15-0.16 €/min (full sample) or even remains constant at 0.17 €/min (EV experts) per month. Thus, the installation of additional charging spots does not imply a higher WTP for reducing the charging duration. The same holds true for the waiting time, where the WTP for a 1-min reduction stays almost constant at 0.81-0.82 €/month (full sample) but fluctuates more for EV experts (0.75-0.93 €/month). Consequently, the number of charging spots does not affect the WTP for charging duration. This result supports Illmann and Kluge (2019) and Globisch et al. (2019), who find that consumers are less concerned about the mere presence and density of charging spots but more concerned about charging duration. This concern is reflected by the estimation coefficients where only the interaction coefficient of charging spots with *8 h charging duration* compared to the base case of *10 min charging duration* is statistically significant. Hence, there seems to be a special significance here. However, the number of charging spots indeed affects the predictive margin for waiting time and charging duration, as all predictive margins decrease with more and more charging spots on site.

Further, the WTP for reducing waiting time is around five times larger than for reducing charging duration. For offering faster charging, charging point operators will not be remunerated as much as for reducing waiting time, which is an important finding as well. Duration and waiting time are both closely related to location because it matters where users wait for the recharge.

4.3 Charging Technology

For charging inductively, participants would pay as much as 6.54-10.42 €/month (on average 8.48 €/month, full sample). Compared to the full sample, EV experts would pay a €2 surcharge for charging inductively (7.96-13.73 €/month, average 10.84 €/month). Thus, EV experts seem to be more comfort-driven because they might know already about the burdens of connecting the cable. Overall, with every additional charging spot, participants are more likely to become indifferent between inductive and cable charging. The question remains why the number of charging spots affects the preferred technology.

4.4 Waiting Time

Our participants are willing to pay a substantial amount to reduce dwelling times. For a 1-min reduction in waiting time at 0-250 charging spots, the full sample's WTP slightly decreases from 0.82 to 0.81 €/month, whereas the EV experts' WTP increases from 0.75 to 0.93 €/month. At first, it seems *paradox* that EV experts would be willing to pay more when charging possibilities increase. Yet, this hints at EV experts' advanced EV experience levels where waiting times are tolerable because they rarely occur due to the sheer abundance of charging possibilities. This relates to certainty of charging point availability as researched by Wolbertus et al. (2018b), and discussed in previous research by the authors (Wolff and Madlener 2019) using the same dataset: the sheer abundance or scarcity of charging spots (near home) available for certain might have influenced the decisions made in this DCE. Thus, as Wolbertus et al. (2018b) conclude, creating certainty about the availability of near-home charging spots should be a policy goal to foster EV diffusion by, e.g., a charging spot booking scheme, which could also enhance the efficiency of connection time and occupancy time (Wolbertus et al. 2018a). More specifically, respondents of Philipsen et al. (2016) are more willing to make a detour than accepting waiting times, while respondents in Sun et al. (2016) are willing to make a detour to reach a fast-charging spot than accepting longer charging duration. We show that waiting time is closely linked to the charging location since charging spot demand is also a spatial-temporal issue.

As discussed above, the WTP for reducing charging duration is five times smaller than for reducing waiting time. Charging point operators earn more by reducing waiting time than by accelerating charging speed. Since the WTP for reducing waiting time is also independent from existing charging spots, the installation of additional charging spots will not increase payoff except for EV experts where WTP increases by around €0.04 per 50 charging spots. Analogously to duration, and strangely enough, all predictive margins decrease with more and more charging spots on site. Further, all WTP values are higher than calculated in a previous WTP analysis on the same DCE data without interaction terms (Wolff and Madlener 2019).

4.5 Share of Renewables

Respondents are willing to pay around 0.40-0.50 €/month for improving the share of RES by 1%. This choice behavior reflects the overall tendency towards pro-environmental travel behavior observed in the underlying survey (Wolff and Madlener 2019) as well as the demand for green electricity used for EV charging (Fabianek et al. 2019; Nienhueser and Qiu 2016; Degirmenci and Breitner 2017). With every additional charging spot, participants are more likely to opt for a higher share of RES. The question remains why charging spot availability has an impact on the preferences for RES. It could be that the higher is the number of charging spots and thus the population density, the higher is the degree of environmentalism.

4.6 Charging Costs

Overall, our results remain intuitive with the strongest preferences for lower costs. Compared to the other attributes, the confidence intervals are very small. Thus, costs remain important and there is hardly any variation in the choice behavior. Even with increasing charging spot quantities, we observe the largest differences between the four cost attribute levels. Respondents seem to choose very distinctively between the four cost attributes. According to the smaller marginal effects, EV experts put less emphasis on lower costs than the full sample.

The cost coefficients (i.e. the main and interaction effects) determine every WTP by means of the nominator in eq. (9). Thus, it depends on the size and sign of the cost coefficients whether the WTP decreases or increases with every additional charging spot. Through their choices with respect to costs, participants also determine their monetary valuation of the other five attributes subject to the number of charging spots. Costs are the integral ingredient of this DCE, along with the number of charging spots.

4.7 Policy Recommendations and Future Research

The spatial heterogeneity reveals that the non-availability of public charging spots affects the choice probability more than the general existence of charging spots. Further, respondents become more and more indifferent between the attribute levels the more charging spots there are, e.g. the awareness of 0 or 1 charging spot/s is higher than for 1 or 2 charging spot/s. This could be further evidence of charging point awareness where charging spot awareness or availability does not imply immediate proximity to the household or to the neighborhood. Similarly, the charging spot density, i.e. charging spots per area or per EV, might not be an appropriate proxy for charging point availability. Our results support previous findings that consumers are less concerned about the mere presence or density of charging spots but more concerned about costs, location, duration, and waiting times. Thus, from a policy perspective, our results suggest a need for (affordable fast-) charging spots primarily at home (either on private properties or public charging spots in residential areas) or at work (i.e. in mixed-use areas) which can be booked in advance. These results are supported by Chakraborty et al. (2019) who state that policies need to be aimed at the individual’s tradeoff between monetary incentives and convenience in order to limit the shift from home to work or public charging, e.g. since the installation of public charging infrastructure is more costly than at-home chargers. Then, it is interesting to see whether the installation of additional public charging spots actually pays off through a higher WTP for charging at the preferred location. Also, the shift from daytime to nighttime charging would lift the burden of higher demand from energy utilities and would ease the integration of renewable energies into the grid by flattening peak demands during daytime. The discussed corresponding confidence intervals give possible price ranges for EV charging infrastructure services.

Moreover, location is closely linked to waiting time. Our results suggest that charging point operators could charge a price premium for reducing waiting time than for accelerating charging speed. To raise charging spot availability, a reservation system could be implemented. The booking of charging spots in advance would enhance the respondents' reliability on finding a spot outside their homes. Also, dynamic pricing strategies could incorporate the sole cost of vehicle parking (Chakraborty et al. 2019). This price premium might reduce the shift from at-home to public charging. All these policy measures might enhance EV sales and thus EV usage and reduce charging spot congestion. There could be other important time-(in)variant unobserved individual characteristics that we were unable to consider but which could be addressed in future research.

5. Conclusion

In this study, we spatially map the willingness to pay for charging options according to the (non-) availability of public charging spots by matching a DCE with a data set of publicly accessible charging spots. We find spatial heterogeneity in the WTP for different attributes of the charging process in correlation to the number of charging spots available in those regions. Respondents' choices depend on the quantity of charging spots available in the area they live in. Thus, they are somewhat aware of charging spot quantities locally available to them. This may be further evidence of charging point awareness. Yet, with every additional charging spot, the less distinctive become the differences between the attribute levels in the choice behavior. Our results support previous findings that consumers are less concerned about the mere presence or density of charging spots but more concerned about costs, location, duration, and waiting times. The most integral part of this study is the analysis of the interaction of charging location with the number of public charging spots. An increase in charging spot availability increases respondents' willingness to charge away from home, also among non-EV owners. This holds until the number of charging spots has reached a tipping point at which respondents become indifferent between at-home and at-work charging. When the tipping point is exceeded, respondents rather charge at work than at home. Thus, with increasing numbers of charging spots, public charging spots near home are less relevant than those in the work neighborhood.

Further, our results reveal a fivefold higher WTP for reducing waiting time (for a charging spot to become available) than for accelerating charging speed. Thus, charging point operators could earn more by implementing a booking scheme than for implementing fast-charging. We report the corresponding confidence intervals in order to discuss possible price ranges for EV charging infrastructure services. From these apparent EV consumer needs one can derive some business model ideas and recommendations for planners of charging infrastructure and policy makers, but also reveal possible pitfalls and common misinterpretations.

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