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An experimental analysis of consumer preferences towards public charging infrastructure

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ABSTRACT

As the share of battery-electric vehicles (BEVs) in car fleets increases, more and more car holders will need to charge their electric vehicles at public facilities. Designing public charging infrastructure so as to make it attractive to current and future BEV holders thus becomes essential. We implemented a choice experiment with a large sample of current BEV (N = 950) and non-BEV (N = 1,881) holders to examine the relevance of several design features that are widely presumed to be important in this regard: waiting (queueing) time, charging time, price, energy source, and amenities. Mean queueing time turns out to be most relevant, and car holders are also willing to pay for limiting or avoiding (uncertain) queueing times. The main implications for commercial and public charging infrastructure providers are that they should seek to provide fast charging, real-time observability of charger occupancy, and the opportunity to reserve chargers.

1. Introduction

Replacing internal combustion engine vehicles (ICEVs) with fully battery electric vehicles (BEVs) can help enhance local air quality, reduce greenhouse gas emissions, save energy, and reduce dependence on fossil fuel imports (Ashkrof et al., 2020; House & Wright, 2019; Huang & Kockelman, 2020). One of the key obstacles to increasing the share of BEVs in car fleets pertains to limitations of charging infrastructure. Most daily travel needs that are met by individual motorized transport can, in most countries, be accomplished with current BEV ranges (Melliger et al., 2018), mainly because battery technology has advanced well over the past few years (Nykvist & Nilsson, 2015). However, existing research shows that range anxiety and concerns about the availability of and access to (fast) charging infrastructure (Axsen et al., 2016; Egbue & Long, 2012; Skippon & Garwood, 2011), particularly for longer distance travel and for car holders without private parking, are key reasons why many people are still reluctant to adopt BEVs (Coffman et al., 2017; Daramy-Williams et al., 2019; Hardman et al., 2018; Li et al., 2017; Liao et al., 2017; Pettifor et al., 2017; Rezvani et al., 2015; Singh et al., 2020; Wicki et al., 2023).

We contribute to the literature on these barriers to BEV uptake and longer BEV trips (such as weekend or holiday trips, longer business trips) by assessing the charging preferences of both potential and current BEV users. Specifically, we focus on key characteristics of public charging stations that are likely to be important from the viewpoint of users. Previous research has found that home charging opportunities are highly relevant for early adopters of BEVs (Brückmann et al., 2021b; Figenbaum & Kolbenstvedt, 2016; Hardman et al., 2018; Klein et al., 2020), who prefer home charging, but are not attainable for all potential user groups (such as people

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living in flats and relying on unmanaged on-street parking), as well as, some longer BEV trips warrant public charging options to make full use of BEVs (Brückmann & Bernauer, 2020; Funke et al., 2019; Globisch et al., 2019; Wicki et al., 2022). We advance previous research by focusing on time, notably in the sense of (uncertain) queueing time for chargers to become available, and on charging time as such. We look at these two concepts of time jointly, based on a choice experiment that also considers other features, such as price, energy source, and amenities, presented to large samples of BEV holders (N = 950) and non-BEV holders (N = 1,881). Therefore, we go beyond previous research focusing on BEV holders only (Visaria et al., 2022). An additional novel experiment assesses whether and how much users would be willing to pay for reserving a charging station, which is the most obvious measure for reducing uncertainty and limiting queueing time.

To date there has been very little research on these issues, though more insights on them will be crucial both from a private and public sector perspective. Many public charging facilities are likely to be owned and operated by private entities, and these are likely to compete to an increasing degree in trying to attract customers. Policymakers, in turn, will be interested in electrifying the car fleet within the next decade or two. This is more likely to succeed if the charging infrastructure meets the expectations of its users, as public and private entities are currently planning to invest on a large scale in public charging infrastructure. One example is the European Union, which envisages a strong expansion of public charging networks in its “Fit for 55” program (Sperka, 2021), with an emphasis on fast chargers along highways (Morrissey et al., 2016). The reason for the latter is that fast charging appears to be preferred for its convenience by current BEV users with large battery capacity (Wolbertus & van den Hoed, 2020) and because distances driven by BEVs are increasing (Yang et al., 2020b). Nevertheless, as previous literature provides relatively few insights into actual or potential user preferences for public charging infrastructure, we address this issue in the present paper.

Providing car holders with adequate charging infrastructure is key to making BEVs attractive (Cole et al., 2021; Ledna et al., 2022) to those seeking to replace their conventional car with a BEV and is likely to prevent the discontinuance of BEV ownership among existing BEV holders (Hardman and Tal, 2021). Existing research on this issue focuses mainly on how relevant charging infrastructure is to individuals’ propensity to acquire a BEV and to what extent the public prefers governments to fund such infrastructure (Anderson et al., 2018; Baumgarte et al., 2021; Brückmann & Bernauer, 2020; Burnham et al., 2017; Globisch et al., 2019; Greene et al., 2020; Hardman et al., 2018; House & Wright, 2019; Ito et al., 2013; Jochem et al., 2016; Kumar et al., 2021; Miele et al., 2020; Schroeder & Traber, 2012; Serradilla et al., 2017; Wolbertus et al., 2020; Zhang et al., 2018).

The remainder of the paper is structured as follows. The next section discusses the existing literature on BEV charging infrastructure preferences, followed by information on the study design and data. We then present the empirical findings and end by discussing their policy relevance and options for further research in the concluding section.

2. Arguments and empirical expectations

In this section, we discuss the existing literature on BEV charging infrastructure and theoretical arguments with respect to features of charging infrastructure that are likely to be relevant to consumer choices. Based on this, we outline empirically observable implications to be tested in our experiment.

More and more BEV models arrive on the market, battery and electric vehicle prices are falling, and price parity to conventional vehicles is expected sometime soon (Mahmoudzadeh Andwari et al., 2017; Nykvist & Nilsson, 2015; Nykvist et al., 2019; Ziegler & Trancik, 2021). Nonetheless, the market uptake of BEVs remains rather slow for the time being, creating major challenges for the rapid decarbonization of road transport. Limited charging infrastructure is widely regarded as a critical obstacle to overcome in this respect. The reason is that faster and more convenient charging is likely to reduce what are arguably the key obstacles to BEV adoption, namely range anxiety and the inconveniences associated with longer queueing and refueling (recharging) times, compared to conventional vehicles (Ardeshiri & Rashidi, 2020; Egbue et al., 2017; Ghasri et al., 2019; Greene et al., 2020; Neaimeh et al., 2017; She et al., 2017).

Charging station congestion and queueing have, to some extent, been examined in the existing literature (Ashkrof et al., 2020; Hassler et al., 2021; Huang & Kockelman, 2020; ten Have et al., 2020; Wang et al., 2021; Yang et al., 2020a). However, we do not know of any study that has clearly distinguished between charging and waiting (queueing) time, alongside other charging infrastructure properties that are likely to determine the attractiveness of such infrastructure from a (prospective) user perspective. It is noteworthy that existing public and proprietary real-time information systems are, to varying degrees, supporting BEV holders in trying to find available charging stations. One example is the system by Tesla, see Appendix Figure A. Nevertheless, while operators of such systems may have proprietary information on how charging infrastructure is used and what their users may or may not prefer, there are no published scientific studies on this issue. Insights into what properties of charging stations are more (or less) relevant to actual and potential users may help improve such systems both in the public and private domain.

This paper focuses on prolonging BEV trips and facilitating trips beyond BEVs’ typical driving ranges (Ardeshiri & Rashidi, 2020; Ghamami et al., 2020) because this is widely regarded as a critical bottleneck in BEV adoption and use. For shorter trips, the energy stored in a given battery is usually sufficient under all weather conditions (Ghamami et al., 2020). Most BEV holders know this – though non-BEV holders may be less aware of this (Brückmann, 2022b).

It is widely presumed that fast charging is preferred by most BEV holders for longer distance travel, away from home or the workplace (Wolbertus & van den Hoed, 2020; Yang et al., 2020b). Only the fastest charging infrastructure (level 3 charging) can provide this level of service (Nie & Ghamami, 2013), which delivers energy for around 160 km (100 miles) in under 15 min and is typically found on corridors (Hardman et al., 2018; Jochem et al., 2015; Morrissey et al., 2016). Hence, we examine whether charging infrastructures’ attractiveness (choice probability) increases with shorter charging time (alongside variation in queueing time and uncertainty over the latter).

H1: *We expect shorter charging time to be positively related to charging station choice.*

Existing research has focused mainly on deploying more charging stations and increasing charging speed (Ardeshiri & Rashidi, 2020; Ghamami et al., 2020) to reduce range anxiety. We add to this literature by considering ways to reduce idiosyncratic queueing (waiting) times for chargers to become available, which the existing literature has not systematically addressed (Ashkrof et al., 2020; Hassler et al., 2021; Huang & Kockelman, 2020; ten Have et al., 2020; Visaria et al., 2022; Wang et al., 2021; Yang et al., 2020b). However, most of the existing research on BEV charging does not differentiate between congestion and other reasons for the total amount of time needed for the charging process. Because waiting-time aversion could be alleviated with reservation systems, whereas charging time aversion can only be mitigated via fast chargers, more insights into how consumers evaluate these two time components will be useful both for public authorities and commercial providers of charging infrastructure.

For a start, we presume that individuals do not consider charging time more critical than mean queueing time. However, assuming that most people are, to varying degrees, risk-averse, we seek to identify whether and to what extent measures to reduce (uncertainty about) queueing time could make charging infrastructure more attractive.

H2: *We expect longer mean queueing time to be negatively associated with charging station choice.*
H3: *We expect more uncertainty about queueing time to be negatively associated with charging station choice.*

In terms of reducing greenhouse gas emissions, it is widely accepted that BEVs should be charged with electricity from renewables (Fabianek et al., 2020; Luo et al., 2020; Priessner & Hampl, 2020; Zhang et al., 2018). It thus appears plausible that being able to charge BEVs with such electricity is likely to make such chargers more attractive, at least from the perspective of current BEV holders, who tend to hold stronger pro-environmental attitudes than current non-BEV holders (Brückmann et al., 2021b; Wicki et al., 2023). However, the existing literature does not offer systematic information on how important the energy source is to users relative to other charging station features (Kacperski & Kutzner, 2020).

H4: *We expect renewable energy sources, such as solar, wind, and hydropower, to be positively associated with charging station choice, whereas nuclear power is likely to make chargers less attractive.*

Charging a BEV away from home or work is commonly regarded as a nuisance, at least relative to the few minutes it takes to refill a fossil-fuel vehicle. This has resulted in discussion on whether providing amenities for shopping or refreshment could, as one might expect (Hypothesis 5), make users more accepting of idle time while charging. With the exemption of Visaria et al. (2022), the existing literature offers no systematic insights into how much amenities are valued relative to other factors that shape charging station attractiveness (Morrissey et al., 2016).

H5: *Charging infrastructure with associated amenities is likely to be more attractive.*

Finally, charging costs as such are likely to matter, as noted for instance by Visaria et al. (2022). Following conventional economic logic, we expect lower charging costs to make chargers more attractive.

H6: *The attractiveness of charging infrastructure is likely to decrease with increasing charging costs.*

3. Data and methods

3.1. Data

Based on administrative data from Swiss car registries, we sampled both conventional car holders and current BEV holders. 20,000 conventional car holders and a census of 2,627 BEV holders were invited to participate in a mixed-mode survey (Brückmann, 2022a;

Table 1
Overview of survey participants for both panels that were combined in 2020, when the choice experiment reported in this paper was implemented.

Survey	Year	2018	2019	2020
Conventional car holders	Responses	4,147	2,226	1,953
BEV holders	Responses	1,178	–	943

Table 2
Overview of survey participants' main demographics, by BEV status at time of experiment.

Variable	Overall	Non-missings	BEV households	Non-missings	Non-BEV households	Non-missings
Age as of 2020 in years (mean)	57.4 (SD 13.5)	n = 2,815 (16 missing)	56.8 (SD 11.8)	n = 937 (13 missing)	57.7 (SD 14.3)	n = 1,878 (3 missing)
Female (share)	0.30 (SD 0.5)	n = 2,815	0.17 (SD 0.38)	n = 937	0.36 (SD 0.48)	n = 1,878
Tertiary education (share)	0.45 (SD 0.5)	n = 2,812	0.59 (SD 0.49)	n = 935	0.39 (SD 0.49)	n = 1,877
Household income (share)		n = 2,601		n = 872		n = 1,729
< CHF 4,000	0.03		0.01		0.04	
CHF 4,000–8,000	0.26		0.16		0.31	
CHF 8,000–12,000	0.31		0.29		0.33	
CHF 12,000–16,000	0.19		0.23		0.17	
> CHF 16,000	0.21		0.31		0.15	

Table 3
Charging station characteristics in the experiment (choice attributes and attribute levels).

Attribute	Attribute levels
Facilities/Amenities	None (paved parking lot) / Yes (shop, coffee shop, small patch of grass with bench and washrooms
Charging Time	30 / 60 / 90 min
Energy Source	Nuclear / solar / hydro / wind
Price (for the whole recharging process)	5 / 10 / 15 / 20 / 25 / 30 CHF[2]
Queueing Time	Random combination of *either* two *or* three values, constructed as follows: 0 or 5*x min (with ×, ∈ {ℕ+} × ≤ 8) or 0 or 5*x or 5*y (with × ≠ y, x, y ∈ {ℕ+} × ≤ 8, y ≤ 7)

[2] 1 CHF (Swiss Franc) = 1.08 USD (US Dollar) as of January 24, 2023.

Brückmann & Bernauer, 2020; Brückmann et al., 2021b). This data transfer followed local data protection law and the survey was approved through ETH Zurich's institutional internal review board (EK 2017-N-85). We did not place any restrictions (e.g., on age, gender) on eligibility to take part in these surveys nor did we apply any quotas.

Based on these two samples, two panels were created, as displayed in Table 1. In October and November 2020, we administered an online survey[1] wave with these panels that involved 3,046 car holders and featured the choice experiments on which this paper centers. Other parts of the survey dealt with BEV and solar PV ownership (Brückmann, 2022a), resale values (Brückmann et al., 2021a) as well as individual impacts of the COVID-19 pandemic. The complete survey instrument can be found under the link provided under "Data availability".

While not all respondents took part in the choice experiment in full due to a lack of explicit consent or item non-response, pooling both panels resulted in 2,831 observations with complete information, also on BEV ownership: 950 individuals with BEVs in their households in 2020, and 1,881 without. 893 of those with BEVs are from the originally recruited BEV panel, the remainder (57) is from the other panel. 29 persons from the BEV panel reported no BEV (which includes individuals without any car or item non-response). In the remainder of the paper, we report on BEV ownership status at the time of the choice experiment. Table 2 provides key descriptives (collected in the first panel wave) for all participants in the choice experiment. Including, and distinguishing, both BEV and non-BEV holders allows us to identify whether presumably greater familiarity of BEV holders with charging infrastructure is associated with differences in what factors matter more in making charging infrastructure more (or less) attractive.

Because these two samples are inherently different, we will only in some instances report results for them jointly.

3.2. Method

To test the above hypotheses, we implemented a binary choice experiment. The experiment was prepared in R (R Core Team, 2018), employing a full-factorial design, and was implemented in a commercial survey programming environment. Specifically, we use a Referendum Choice Experiment (RCE), as previously applied in the context of BEVs in Australia (Ardeshiri & Rashidi, 2020).

The key variables that are experimentally manipulated are thus charging time, queueing time, energy source, price, and facilities/amenities. These variables and the values they can take in our experiment are shown in Table 3.

All attributes and attribute levels were guided by theoretical considerations and our desire to advance knowledge on BEV charging

[1] We only contacted people who indicated a willingness to be in the respective panel in the previous wave by regular mail or email, depending on their mode-of-contact preferences. In their survey invites, they received a link to the online survey. The survey was programmed and performed through the Qualtrics (https://www.qualtrics.com) online survey tool. Up to two reminders were used to contact respondents who didn't answer the survey after the invitation. Panelists had the opportunity to call or mail the research team with any technical questions or to opt-out of the panel at any time.

Features	**Charging Station A**	**Charging Station B**
Energy source	Wind power	Solar energy
Price	CHF 25	CHF 10
Surrounding **amenities**	Shop, coffee place, small lawn area with park bench, and toilet	Paved parking lot
Charging time until battery is fully charged	30 minutes	60 minutes
Queuing time until charging spot empties (can be either with the same probability)	0 minutes or 10 minutes or 30 minutes	0 or 15 minutes

Would you charge at station A or station B?

Fig. 1. Example of a choice task.

options that might promote BEV uptake and usage. We base our choices for these values on a combination of previous research, as described above, focus group discussions conducted in November 2019 (Wicki, Brückmann & Bernauer, 2022), as well as discussions with participants in studies with electric vehicle test-drivers (Brückmann, 2022b, 2022a). For example, for queueing times, we combined qualitative information about times mentioned by potential BEV buyers with values reported in the literature. For example, Wang et al (2021) utilizes 0, 15, or 30 min for potential queueing times.

Please note that, because electricity production in Switzerland, where this experiment was performed, is based exclusively on non-fossil fuel sources (Swiss Federal Office of Energy (SFOE), 2021) and Switzerland seeks to decarbonize its economy by 2050 (Swiss Federal Office of Energy (SFOE), 2020), we omit fossil-fuel based electricity from our experiment, though adding this in experiments in other countries will of course be important.

This choice experiment mimics a scenario where an app or onboard navigation system proposes different charging points (Kacperski & Kutzner, 2020). The user must then decide which of the proposed charging stations to select. In this experiment, potential detours, which have previously been shown to influence the decision for charging points (ten Have et al., 2020; Yang et al., 2016), are intentionally held constant.

Thus far, queueing times (or waiting times for occupied chargers to clear) have mostly been treated in a deterministic fashion (Wang et al., 2021). We introduce a stochastic component because, in the absence of a reservation system, it is very likely that there will be some uncertainty about how long a queue will be upon arrival. Some previous model-based (rather than empirical) research (Alizadeh et al., 2014) has considered uncertainty, and a few studies (e.g., ten Have et al., 2020) have included uncertainty in a dichotomous way (certainty or uncertainty if a charger is unoccupied) and found that it matters for charger choice. We explore this in more detail, based on different potential queueing times with different probabilities.

Previous research found that perceptions of a comfortable range can help explain the charge level at which BEV holders usually recharge (Franke & Krems, 2013). This finding is also in line with research showing that the initial charge level explains charging choice among BEV owners (Ashkrof et al., 2020; Yang et al., 2016). We abstract from these notions and offer respondents charging

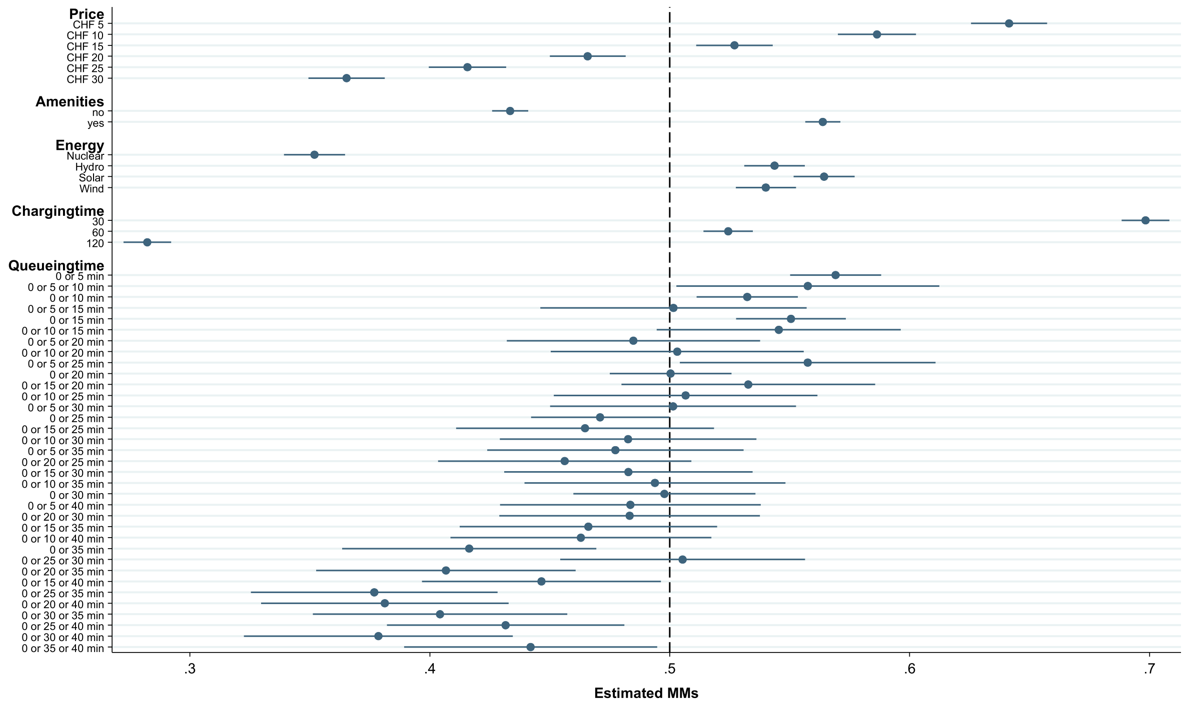

Fig. 2. Marginal means for n = 1,881 respondents without a BEV. Point estimates higher than 0.5 indicate that the probability of respondents selecting a charging station that has this particular attribute value (while all other attributes can take any value) is larger than 50 %. Horizontal lines around the dot (point estimate) indicate 95 % confidence intervals.

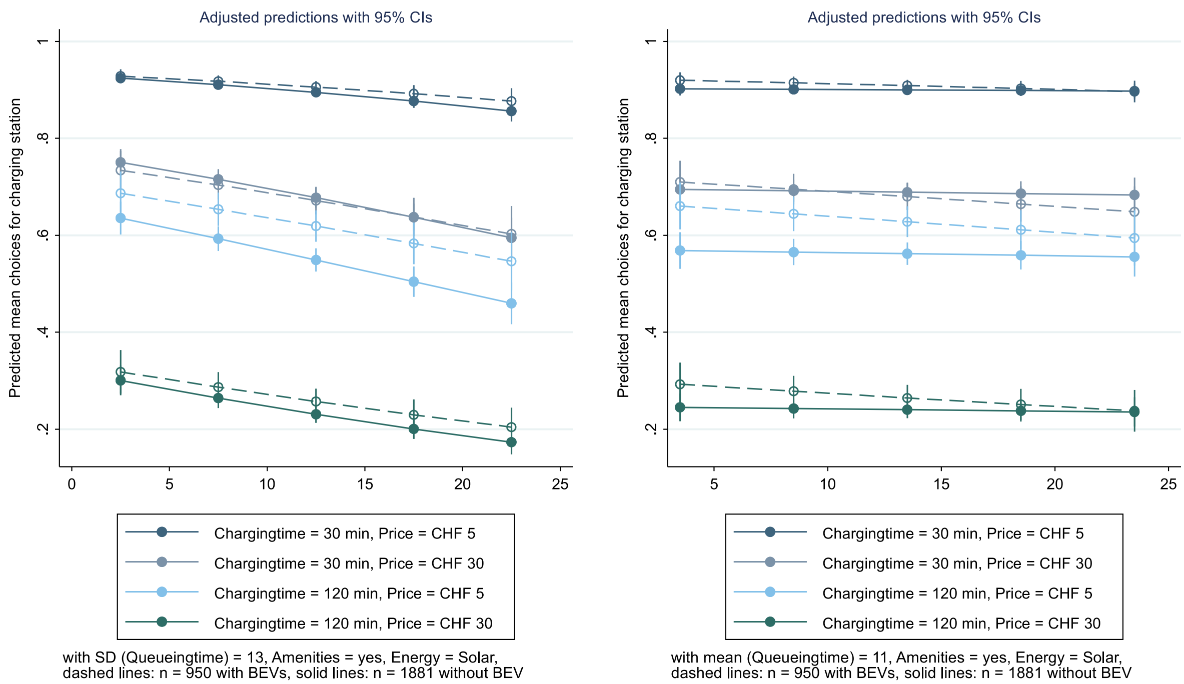

Fig. 3. Predicted choice probabilities with 95 % confidence intervals indicated by vertical lines (whiskers) around point estimates. All choices keep amenities present and energy at solar while varying over mean queueing time (in the left panel) or over the standard deviation of queueing time. Shorter charging time (faster charging) moves the lines upwards, whereas higher price moves the lines downwards.

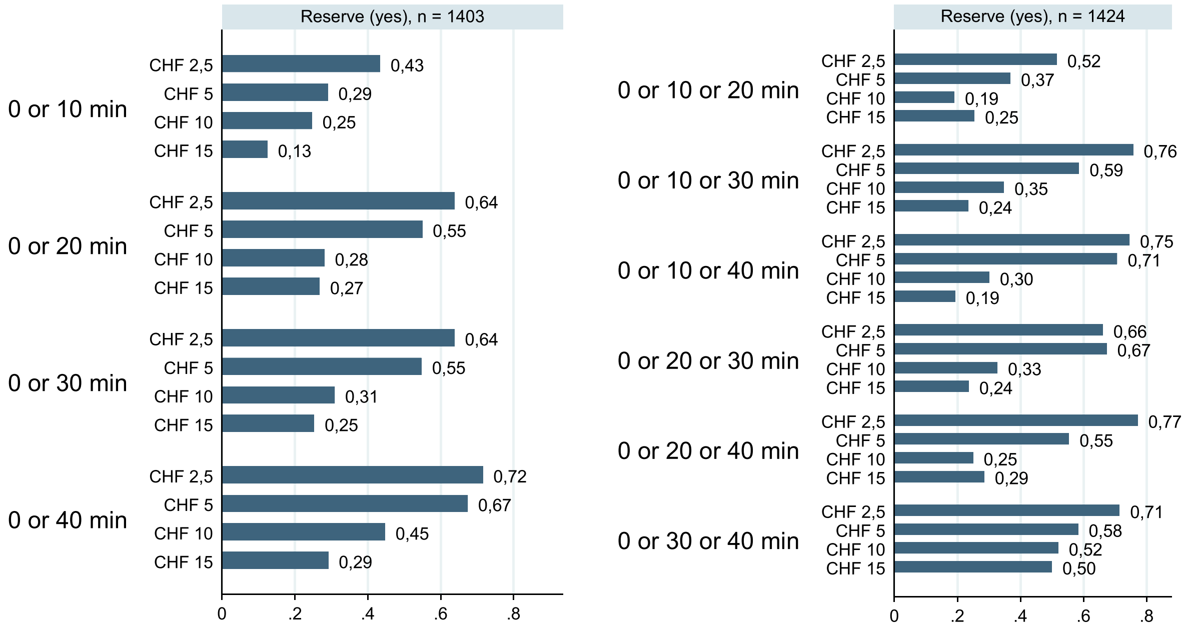

Fig. 4. Main findings from the vignette experiment on charger reservation. Bars show the share of respondents who would purchase a reservation for different potential queueing times at different prices.

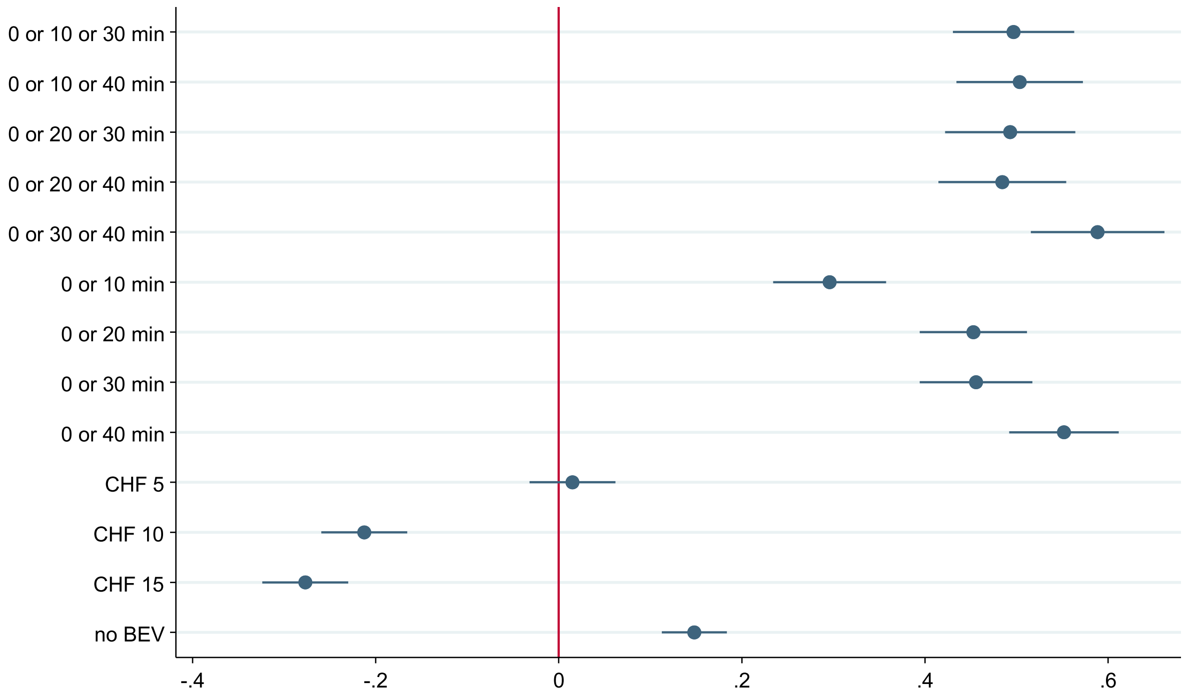

Fig. 5. Coefficients and 95 % confidence intervals (horizontal bars) for OLS regression of choice for reserving a charging station for given queueing times and prices.

options to complete their trip, independent of the charge level at which they would consider recharging. We present this scenario in the same way to BEV and non-BEV holders (Pevec et al., 2020).

Study participants were introduced to the choice experiment as follows: "*In the following, we would like to ask you a few questions about charging electric cars.*

Please read the following text first. We will then ask you some questions about it.

*Imagine the following situation: You are driving an electric car (exclusively battery electric powered car, no hybrid car) and have reached a low charge level of your battery (below 25 km remaining range). This battery level is no longer sufficient for the remaining distance to your destination. Your navigation device now suggests two charging stations for your electric car that you can reach with your current battery level to charge your vehicle. Both charging stations are in the direction of your travel and are at the same distance (10 km) from your current location. You must now choose one of the two charging stations. At both charging stations, you can pay by card (*e.g.*, some examples of locally popular cards), by smartphone (*e.g.*, examples of locally popular money transfer apps) or by cash. A pre-registration or a specific application on your mobile phone is not required.*".

This introductory text was accompanied by a graphical illustration depicting an electric car with a 25 km range remaining and two charging stations at a 10 km distance in the direction of motion.

Each respondent was asked to choose five times between two different charging stations, as illustrated in Fig. 1. This resulted in 28,310 observations (n = 2,831 * 5 iterations * 2 stations).

We use Average Marginal Component effects (AMCEs) to study the effects of different attributes on the choice of charging stations (Barari et al., 2018; Hainmueller et al., 2014). We also provide Marginal Means, allowing for sub-group comparisons (Leeper et al., 2020), such as car holders with or without BEVs. These statistical estimation approaches treat all attribute values as nominal by using multiple dummies. Because we have two values (price and charging time) that could be regarded as metric, we treat them as such in logistic binary choice models. We use logistic choice models to estimate the influence of different attributes and the mean and standard deviation of the idiosyncratic queueing time until a charger becomes available at the station. This means that, besides looking at all the levels of queueing time only, as presented to the respondents, we also analyze them in terms of the mean and standard deviation of expected waiting times. The distribution of waiting times is fully described by the mean and standard deviation.

In an additional experiment within the same survey, we elicited preferences for queueing time reductions by means of reservation of a charging station prior to arrival. We designed a vignette experiment that directly followed the charging choice experiment. We randomly assigned prices (either 2.5, 5, 10 or 15 CHF) and varying queueing times (the same possibilities as in the choice experiment described above). Respondents were asked to indicate whether they would purchase a reservation based on a (randomly) given combination of price and expected waiting time.

4. Results

4.1. Main analysis of choice experiment

Fig. 2 summarizes the main findings from the choice experiment, based on the analysis of marginal means for the larger sample of non-BEV holders. This figure aims to illustrate basic trends. The largest change in marginal means is caused by saving 90 min when charging (charging 30 instead of 120 min). This charging time effect is even larger than the effect of increasing price from 5 to 30 CHF. A similar figure for BEV holders can be found in Appendix B, while the differences between the models are depicted in Appendix Figure F.

Overall, the effects of all attributes, such as energy (renewable energy sources preferred), price (the lower, the better), and charging time, are as expected. This means we find support for hypothesis 1 (shorter charging times are positively related to charging station choice). We also find support for hypothesis 4 (renewable energy sources, such as solar, wind, and hydropower, are positively associated with charging station choice, whereas nuclear power is likely to make chargers less attractive), for hypothesis 5 (Charging infrastructure with associated amenities is likely to be more attractive), and hypothesis 6 (attractiveness of charging infrastructure is likely to decrease with increasing charging costs).

Idiosyncratic queueing time (following hypotheses 2 and 3) is, perhaps surprisingly, somewhat less relevant than other attributes in charging station choices. Up to around 15 min queueing time seems acceptable to most respondents, longer potential queueing times have a negative effect on charging station choice.

In addition to analyzing the effects of different combinations of stochastic queueing time, as in Fig. 2, we also use a binary choice model (logit model) to look at the effects of mean queueing time, the standard deviation (SD) of the possible queueing time, as well as the charging price. Fig. 3 illustrates findings shown in more detail in Table in Appendix C. It shows adjusted predictions for the choice of a charging station. In the left panel, we show how different mean queueing time changes choice probabilities, while in the right panel, we focus on the standard deviation of queueing time. We observe that mean waiting time is more relevant, as evident from steeper curves, compared to only very minor differences in the standard deviation of waiting time. Changing from solar energy to nuclear energy, or from the provision of amenities to none always moves the prediction lines downward. The same applies to higher prices and longer charging times.

This additional analysis again supports hypotheses 1 and 4–6. As to hypothesis 2 (longer mean queueing time is negatively associated with charging station choice) we observe that larger mean waiting time is negatively related to charging station choice, whereas higher standard deviations (right panel of Fig. 3) are not statistically significantly associated with a lower probability that a charger is chosen. This means that we find support for hypothesis 2, but not for hypothesis 3 (more uncertainty about queueing times is negatively associated with charging station choice).

4.2. Willingness to pay

Using margins at means, we can also interpret our findings as follows. Reducing charging time by one-minute increases the probability of choosing a charger by 0.005 percentage points (all other variables held at their respective means). A 1 CHF price reduction increases the choice probability by 0.14 percentage points for non-BEV holders, and 0.15 percentage points for BEV holders. A 1-minute reduction in mean queueing time increases choice probability by 0.007 for non-BEV holders and 0.009 for BEV holders. This implies that queueing time is disliked more than charging time. From these results presented in Fig. 3 and in Appendix C, we can estimate BEV holders' willingness to pay for certain features: at mean, BEV holders are willing to pay around CHF 10 for amenities, when solar energy is available, charging takes 60 min, and queueing is at 13 (mean) minutes with 11 min SD, and prices are at their mean (12.5). The different renewable energy forms instead of nuclear are roughly valued at CHF 19.7 (hydro), CHF 23.5 (solar) and CHF 20 (wind). The corresponding values for the non-BEV sample are similar (CHF 10 for amenities, CHF 17.5 for hydro, CHF 18.9 for solar and CHF 16.8 for wind). As the standard deviation of the queueing time has no significant influence on charging station choice, we do not provide willingness-to-pay (WTP) estimates for this aspect.

In Appendix E, we show that the patterns we find for queueing vs charging time cannot be explained by mental laziness of respondents. Specifically, we introduce a dummy that only takes on the value 1 if the queueing time is expressed by only two instead of three values. This variable has no signification effect on charging station choice.

We looked into whether choice patterns differ across respondents with or without a BEV in their household in more detail (see Appendix D). Perhaps surprisingly, we find only minor differences in this respect, similar to the WTP estimates. Substantive differences are only observable for energy source preferences and charging time. BEV holders seem to value renewable energy sources slightly more and are slightly more accepting of longer charging time. However, our substantially different results are also statistically significant, and therefore we should not pool our data from BEV and non-BEV respondents in this choice experiment.

As queueing times are stochastic, we might expect that respondents use heuristics or mental shortcuts when evaluating charging station profiles. In Appendix E, we look at a worst-case scenario, where respondents only pay attention to the maximum waiting time indicated. While maximum waiting time has effects in the expected direction, the maximum queueing model performs worse in terms of AIC than our preferred model, indicating that respondents consider primarily the mean and variance of queueing times.

4.3. Reservation vignette experiment

The vignette experiment on charging station reservation, which was placed directly after the conjoint choice experiment in the survey, shows that around 44 % of respondents prefer to reserve a charging station (40 % of current BEV holders, and 47 % of current non-BEV holders). The somewhat stronger interest in reserving a charging station amongst current non-BEV holders suggests that these individuals are more risk averse, overestimate potential queueing, or are less likely to have home or work charging options and therefore depend more on public charging.

Fig. 4 shows that, except for the case where queueing does not exceed a maximum of 10 min, reservations for CHF 2.5 are attractive for more than half of the respondents. Similarly, reservations for CHF 5 are also chosen for potentially longer queueing times.

Linear and logistic regression estimates support the interpretation of Fig. 4 (see Appendix G). As illustrated in Fig. 5, respondents are more likely to reserve when the waiting time is above 10 min, and the price is 2.5 CHF or 5 CHF.

5. Conclusion

In this paper we examine determinants of (potential) user preferences towards charging infrastructure for BEVs, focusing on charging station characteristics pertaining to price, energy source, charging time, amenities, and idiosyncratic queueing times. We also look into the market potential for a reservation system for charging stations that could serve to mitigate concerns about queueing time and associated uncertainty. We find that it is important to provide fast charging as well as short queueing times at charging stations, and that a reservation system could help in addressing queueing time and associated uncertainty concerns. These findings speak to previous research suggesting that BEV adoption is responding to improved charging infrastructure (Illmann & Kluge, 2020), particularly in view of BEV holders envisaging longer-distance travel. For instance, our results line up with a finding by Klein et al. (2020) that a reduction of charging times from 90 to 30 min is equal to an increase of home charging availability from 28.3 % to 100 % (Klein et al., 2020). From an electricity-grid operation perspective, it also seems important to take this strong taste for quick charging into account for charger location and operating regimes because out-of-home fast charging usually occurs during peak load time of the grid (Moon et al., 2018).

The findings for charger reservation suggest that such a reservation system may be helpful in addressing the "chicken-and-egg" problem that consumers are not inclined to buy a BEV before there is adequate charging infrastructure, while (potential) providers of BEV chargers do not install attractive infrastructure before there is enough demand (Greene et al., 2020). ICT-based reservation systems, combined with fast chargers, could also make potential and current BEV holders feel more secure in the sense of both predictable queueing and charging times at desired charging locations. Similarly, to reduce queueing times, technology that directs (potential) customers to available chargers, or those with short queueing times, is likely to be attractive from the viewpoint of current and potential BEV holders/users. This would, obviously, also help in reducing range anxiety, presumably a key obstacle in BEV adoption.

Taken together, our findings suggest that policy makers should promote (through regulatory and market-based approaches) fast-charging infrastructure, fueled by renewable energy, as well as ICT systems showing their occupancy and potential queueing. Ideally, no registration should be required, and no barriers should be placed upon payment methods. For increased interoperability, open data from charging stations could be made available to enable third-party providers to offer overviews of idle charging stations and potentially provide reservation options.

Our research has some limitations that could be addressed in further research. First, to keep our research design relatively simple and intuitive for study participants we did not consider additional factors that might also affect charging infrastructure preferences. For example, we did not consider variation in distance/detour (held constant in our experiment), the current state of battery charge, availability of destination charging, ease of payment (held constant in our experiment), and data transfer or subscriptions with charging station company. Also, we did not address factors relating to potential fears about incompatibility between plugs and chargers (Li, 2019). Adding treatment conditions along these lines into experimental study designs for the analysis of charging infrastructure preferences could be insightful.

Second, it would be interesting to look in more depth into the queueing time issue and associated uncertainty. Future research could, for example, explore whether fixed instead of stochastic waiting time or information on mean waiting time is likely to matter more for charging station choices. Modifying our study design to that end would be straightforward.

Third, some of our findings differ between the BEV and non-BEV holding sample (e.g., renewable energy preferences), though the effects of charging infrastructure characteristics on consumer preferences are surprisingly similar overall. It would be interesting to try and account for such differences in greater depth. Moreover, as the share of BEV holders in the car holding population increases at a rather rapid pace, it will be interesting to find out whether preferences of new BEV holders then line up with what we observe for current BEV holders.

Fourth, our study design implicates that all respondents must make a charging station choice. However, individuals who are likely to give up or do not own a car or won't use a BEV for trips beyond its range might never get into this situation. While the decision scenario is set up in a way that makes charging necessary, randomization might have generated some cases where both charging options were so unappealing that respondents might have preferred to not charge at all (though this is very unlikely given the scenario we put them in). Adding an explicit opt-out option might change the results and could be implemented in further research.

Fifth, further research could investigate whether a very efficient navigation system that directs BEV users to available chargers could perform the same function in reducing consumer aversion against (uncertain) queueing time as a reservation system, or whether combining the two within an integrated digital system would be useful.

Finally, it would be useful to explore, ideally based on a similar study design, to what extent our findings are relevant to other countries, e.g., countries with different levels of BEV market penetration.

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Data availability

We have shared the data used to create the results. Data and replication code can be found at https://osf.io/xbhqf/?view_only=9ed604cac4614be8ac318ef71edb5254.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Display of charger occupancy

See Fig. A1.

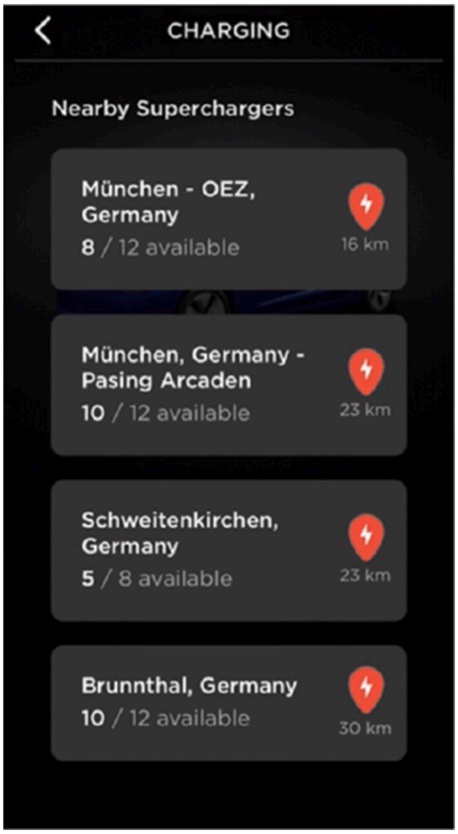

Fig. A1. Screenshot of in-app information showing real-time occupancy and availability of nearby charging stations in the Tesla Supercharger network, serving as an example for a charger occupation information system.

Appendix B. Marginal Means for Households with BEVs

See Fig. B1.

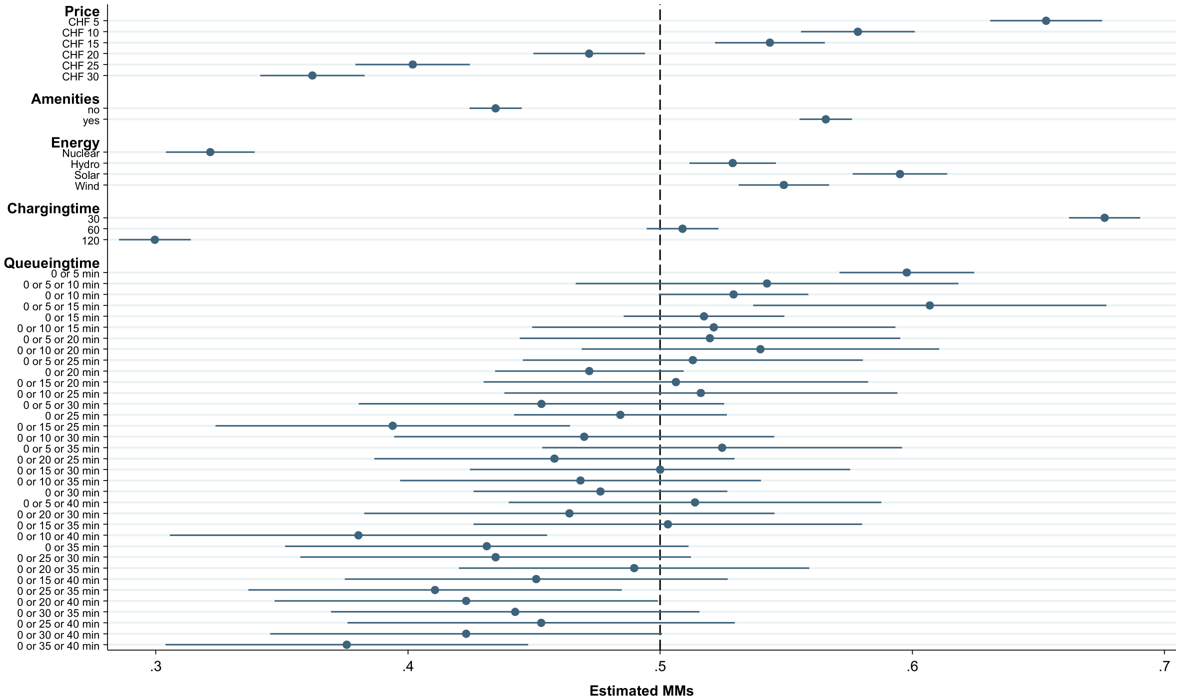

Fig. B1. Marginal means for n = 950 respondents with a BEV. Point estimates higher than 0.5 indicate that the probability of respondents selecting a charging station that has this particular attribute value (while all other attributes can take any value) is larger than 50 %. Horizontal lines around the dot (point estimate) indicate 95 % confidence intervals.

Appendix C. Logit Model for Graphs in Fig. 3 of the Main Paper: Binary Choice for Chargers

See Table C1.

Table C1
Logit regression model for binary charger choice among all respondents, as depicted in Fig. 3. The first model pools all data (not graphically displayed), the second model is only households with BEV, the third model is households without BEV (as depicted in Fig. 3) and Diff. shows coefficients that differ significantly between (2) and (3). The omitted category for amenities is none, and for energy it is nuclear.

Variable	Logit model (all)	BEV only	Non-BEV only	Diff.
Price [in CHF] (5–30 CHF)	−0.06***	−0.06***	−0.06***	*
Amenities: no	(base)	(base)	(base)	
Amenities: yes	0.65***	0.65***	0.65***	
Energy: Nuclear	(base)	(base)	(base)	
Energy: Hydro	1.02***	1.15***	0.96***	*
Energy: Solar	1.15***	1.38***	1.04***	***
Energy: Wind	1.00***	1.17***	0.92***	**
Chargingtime [in min] (30–120 min)	−0.02***	−0.02***	−0.02***	*
Mean Queueingtime [in min] (2.5–25 min)	−0.03***	−0.03**	−0.04***	
Std. deviation Queueingtime [in min] (3.5–24.8 min)	−0.01	−0.01	0.00	
Constant	1.81***	1.70***	1.86***	***
N	28,310	9,500	18,810	

Appendix D. Logit Model for binary choice for charging stations

Our findings for the pooled samples are in column (1), for those without a BEV (2), and those with a BEV (3) indicate that the mean queueing time is highly significant, while the standard deviation is not. This implies that respondents try to minimize mean queueing while accepting large variances. As here the omitted (reference) category is 120 min charging, we can deduct that the effect of charging 60 instead of 120 min (i.e., saving 60 min) is c.p. 1.118, which would mean reducing charging time by 1 min is on average related to 0.01863 while decreasing mean queueing times by one minute is 0.037, which is around double. As this is a non-linear (logistic) model, we cannot directly compare these coefficients in terms of marginal means, as they are local. However, this gives the intuition that stochastic queueing times and deterministic charging times are valued differently. As in the linear case, we again find no difference in queueing time preferences between respondents living in a household with or without BEV, see Appendix D1 Table, column (4) (see Table D1).

Table D1
Logit regression on choice for chargers. The first model pools all data, the second model is households with BEV, the third model is households without BEV and Diff. shows coefficients that differ significantly between (2) and (3). The omitted category for amenities is none, and for energy it is nuclear.

	The binary choice for charging stations (logit models)			
	(1)	(2) BEV	(3) no BEV	Diff.
Price (in CHF)	−0.058***	−0.062***	−0.056***	*
	(0.002)	(0.003)	(0.002)	
Amenities (1 = yes)	0.651***	0.647***	0.654***	
	(0.027)	(0.047)	(0.033)	
Energy = Hydro	1.025***	1.156***	0.966***	**
	(0.039)	(0.067)	(0.047)	
Energy = Wind	1.005***	1.173***	0.927***	***
	(0.039)	(0.067)	(0.047)	
Energy = Solar	1.152***	1.376***	1.046***	***
	(0.039)	(0.068)	(0.047)	
Charging time = 60 min.	1.116***	1.032***	1.158***	*
	(0.033)	(0.058)	(0.040)	
Charging time = 30 min.	1.925***	1.810***	1.986***	**
	(0.035)	(0.059)	(0.043)	
Mean queueing time (min)	−0.037***	−0.037**	−0.037***	
	(0.007)	(0.012)	(0.009)	
SD of queueing time	−0.005	−0.010	−0.002	
	(0.006)	(0.010)	(0.008)	
Dummy for only two numbers in queueing time	−0.026	−0.060	−0.009	
	(0.039)	(0.067)	(0.048)	
Constant	−0.651***	−0.576***	−0.690***	***
	(0.063)	(0.108)	(0.078)	
Observations	28,310	9,500	18,810	
Log Likelihood	−16,408.740	−5,494.134	−5,494.134	
Notes:	*** / ** / * Significant at the 1 / 5 /10 percent level.			

Table D2
Logit regression on choice for chargers. The first model pools all data, the second model is households with BEV, the third model is households without BEV, all models with control variables for age, gender, political leaning and household income. The omitted category for amenities is none, and for energy it is nuclear.

	The binary choice for charging stations (logit models)		
	(1)	(2) BEV	(3) no BEV
Price (in CHF)	−0.057***	−0.061***	−0.056***
	(0.002)	(0.003)	(0.002)
Amenities (1 = yes)	0.659***	0.677***	0.651***
	(0.029)	(0.049)	(0.035)
Energy = Hydro	1.028***	1.131***	0.985***
	(0.041)	(0.072)	(0.050)
Energy = Wind	1.006***	1.134***	0.950***
	(0.041)	(0.072)	(0.050)
Energy = Solar	1.154***	1.357***	1.058***
	(0.041)	(0.073)	(0.050)
Charging time = 60 min.	1.124***	1.035***	1.169***
	(0.035)	(0.061)	(0.042)
Charging time = 30 min.	1.943***	1.822***	2.007***
	(0.037)	(0.063)	(0.045)

(continued on next page)

Table D2 (*continued*)

	The binary choice for charging stations (logit models)		
	(1)	(2) BEV	(3) no BEV
Mean queueing time (min)	−0.039***	−0.044***	−0.037***
	(0.008)	(0.013)	(0.009)
SD of queueing time	−0.003	−0.005	−0.001
	(0.006)	(0.011)	(0.008)
Dummy for only two	−0.028	−0.088	0.003
numbers in queueing time	(0.041)	(0.070)	(0.051)
Year of birth	0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)
Dummy for gender =	−0.011	−0.020	−0.011
female	(0.032)	(0.067)	(0.038)
Political left–right	0.001	−0.009	0.006
(0 to 10)	(0.007)	(0.011)	(0.009)
Household income	−0.016	−0.024	−0.006
(groups, 1–5)	(0.013)	(0.023)	(0.016)
Constant	−2.712	−2.207	−2.855
	(2.087)	(4.097)	(2.435)
Observations	25,210	8,430	16,780
Log Likelihood	−14,589.030	−4,868.716	−9,705.941
Akaike Inf. Crit.	29,208.050	9,767.432	19,441.880
Notes:	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.		

Appendix E. Alternative specification with heuristic that only considers maximum queueing time

As queueing times are stochastic, we expect certain heuristics or mental shortcuts to happen when respondents evaluate the charging station profiles. First, let us assume the worst-case queueing time is what we expect respondents to look at. In this experiment there are 35 different queueing time possibilities and over all of them, the maximum queueing time could be 40 min, which occurs in seven from these 35 possible waiting times. In only one of 35 cases, maximum queueing time is as low as 5 min (see Table D2).

We observe that study participants are quite willing to wait 30 or 60 min for charging, however, are somewhat reluctant to queueing. As Fig. 3 graphically depicts, if waiting time changes from up to 5 min to up to 35 min (i.e., by 30 min), the share of study participants selecting the respective charger drops by 13 percent points. With regards to charging time, the share of study participants drops from 69 % to 51 % when charging time increases from 30 to 60 min, that is 17 % percentage points for 30 min.

Valuing deterministic waiting time reductions more than the maximum queueing time, as the maximum time only realizes for any given queueing time attribute level with $p = 1/2$ or $p = 1/3$ seems legit. Given, however, that the value of a feature, maximum queueing time, that might realize with lower probabilities leads to reductions per minute that are much larger than half the effect of waiting times, leads as to the conclusion that respondents dislike queueing time more than waiting time (see Fig. E1).

We do not consider this model, as this model performs worse in terms of AIC in comparison to our mail model. A full model including both maximum queueing time and mean and standard deviation of queueing time has an associated AIC of 1.161008 and BIC of −257,264.1, while the model with only maximum queueing reported in this Appendix session has an AIC of 1.1617 with associated BIC of −256839.5, while the mean and standard deviation of queueing time model yields AIC of 1.160925 and BIC of −256861.4. Therefore, we conclude a model which considers mean and standard deviation has less information loss and is therefore to be preferred.

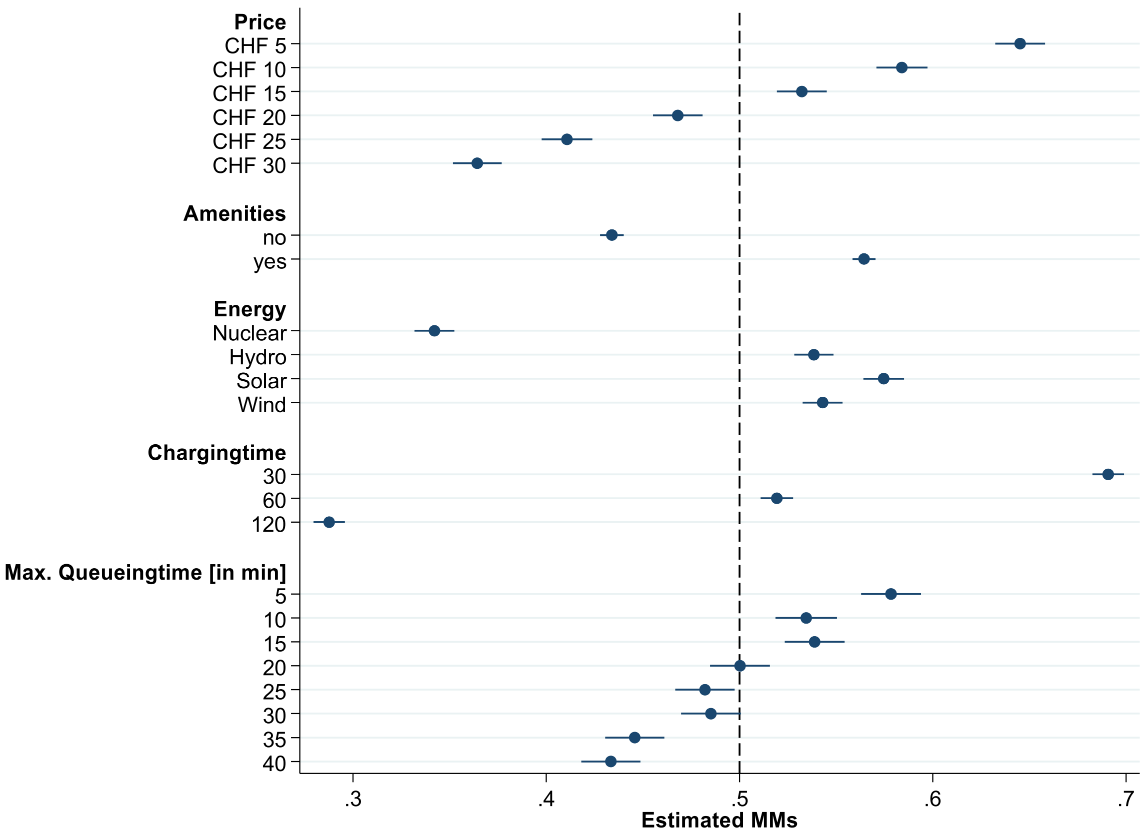

Fig. E1. Marginal Means if respondents only consider longest possible queueing times.

Appendix F. Difference between households with or without BEV

See Fig. F1.

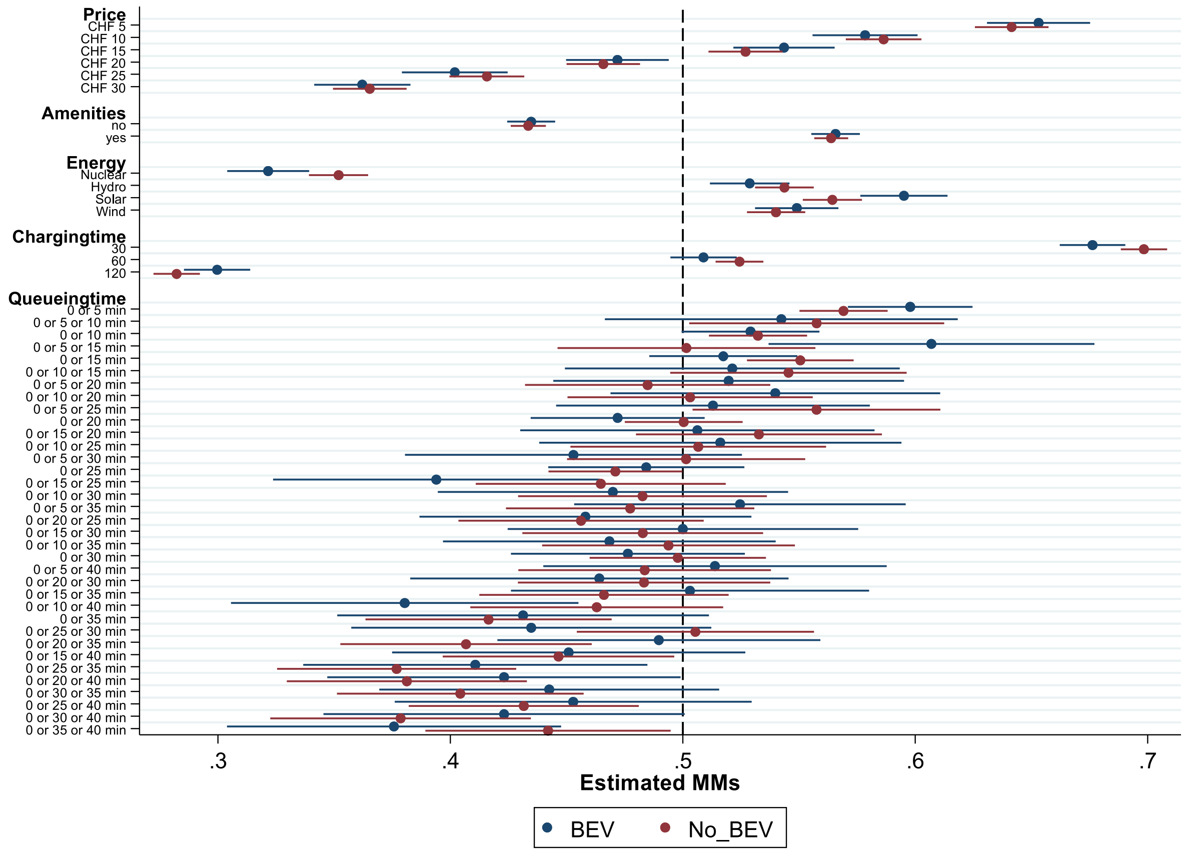

Fig. F1. Differences in Marginal Means between those without and those with BEV at the time of the experiment. Horizontal lines around the dot (point estimates) indicate 95 % confidence intervals.

Appendix G. Logit Regression for Reservation Vignette Experiment

See Table G1.

Table G1
Logit regression on reservation choice.

Variable	OLS model	Logistic regression
Reserve		
0 or 10 or 20 min	(base)	(base)
0 or 10 or 30 min	0.50***	0.64***
0 or 10 or 40 min	0.50***	0.66***
0 or 20 or 30 min	0.49***	0.60***
0 or 20 or 40 min	0.48***	0.58***
0 or 30 or 40 min	0.59***	1.04***
0 or 10 min	0.30***	−0.35*
0 or 20 min	0.45***	0.42**
0 or 30 min	0.46***	0.46**
0 or 40 min	0.55***	0.87***
CHF 2.5	(base)	(base)
CHF 5	0.01	−0.47***
CHF 10	−0.21***	−1.45***
CHF 15	−0.28***	−1.77***

(continued on next page)

Table G1 (*continued*)

Variable	OLS model	Logistic regression
BEV in household		
yes, with BEV	(base)	(base)
no BEV	0.15***	0.29***
Statistics		
N	2827	2827
R^2	0.49	
Adjusted R^2	0.48	

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