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Are consumer preferences for attributes of alternative vehicles sufficiently accounted for in current policies?

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ABSTRACT

International research illustrates some attributes of electro-mobility such as charging infrastructure and range which are crucial determinants of market development. Between 2017 and 2020 the number of battery electric vehicles in Germany has increased much more compared to the number of charging points. High preferences for these attributes in combination with insufficient infrastructure require further clarification to explain why the development of markets for electro-mobility in Germany during the last years is not as expected. This study aims to examine the willingness to pay for attributes of different types of electric vehicles and for car sharing in order to derive recommendations for marketing and policy. The representative study is based on a survey of 405 car users in Germany using a discrete choice experiment with the attributes price, power, running costs, bonus, range and availability of charging stations. 12 choice situations were presented to each respondent. A latent class model was used to analyze socio economic determinants of the willingness to pay for single attributes. The results confirm findings in the literature indicating low preferences for battery electric vehicles in general. Due to high shares of house owners in sub-urban regions this consumer group should be more focused in local sustainability concepts and marketing of battery electric vehicles and other alternative vehicles.

1. Introduction

Global markets for products and services for electro-mobility are changing rapidly. The main drivers are new global, national, and local policies for the reduction of greenhouse gases as well as (EEA, 2018) changing mobility behavior of citizens, especially in cities (EEA, 2018). In 2020 the sales of battery-electric vehicles in the EU, UK and EFTA countries increased strongly to 745,684 and the sale of plug-in hybrid vehicles has grown to the number of 619,129. Germany is by far the biggest market in Europe for electric and plug-in vehicles. In 2020 the European market for battery-electric vehicle (BEV) and for plug-in hybrid vehicle (PHEV) is with nearly 1.4 million cars the biggest worldwide followed by China. The German market is with 398,000 BEV and PHEV the biggest in Europe followed by France (194,000) and Norway (108,000) (Irle, 2021). Markets for electrified vehicles developed contrary to the weak overall European new car market. Mainly due to the COVID19 pandemic, the total European new car market decreased by 24%, whereas electrically-chargeable vehicle sales increased by 143%. The market share increases from 3.6% in 2019 to 11.4% in 2020 (Car Sales Statistics, 2020). The high growth rates for BEV of 6.2% and for PHEV of 5.2% in 2020 indicate a new setting in the mobility sector. However, particularly in Germany the market shares for BEV and PHEV are far behind the policy goals formulated in the master plan charging infrastructure of the federal government (Federal Government, 2020) and behind the public expectations. Achieving these goals requires adaption of business models for products and services to foster the uptake of electro-mobility (McKinsey, 2016).

Innovative business models need to consider various requirements on environmental impacts such as pollution and resource consumption and technological constraints such as range and charging infrastructure for electro-mobility. Current research on electro-mobility focus on two core areas: Firstly, technology-oriented research examining technological solutions for specific applications such as sufficient charging station infrastructure (Jiao and Evans, 2016). Secondly, social science research explores attitudes and preferences of current and future users for technology innovations in the mobility sector, in particular, changes in demand for mobility solutions and acceptance of new technologies for mobility services (Axsen et al., 2015). Further research is required for the various market effects of electro-mobility

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on existing business models for different car sharing models and multi-mobility options and dynamic developments (McKinsey, 2016: 24-27). Furthermore, public regulation of mobility behavior can be used as multiplier for setting incentives. A more detailed consideration of consumer preferences for single attributes of comprehensive mobility concepts is crucial for the application of innovative business models, and to describe the required economic and societal transformation.

Sustainable supply of BEV and electro-mobility services require, first, detailed knowledge on individual preference structures for single attributes of products and services for electro-mobility, and second, investments in improvements of those attributes with currently weak performance. There is evidence that the conditions of sensitive attributes such as range, charging infrastructure, and usage costs have strong impacts on the competitiveness of alternative mobility products and services (Carteni et al., 2016; Giansoldati et al., 2018). Preferences for single attributes of sustainable mobility vary significantly between different consumer groups.

In particular, range, charging infrastructure, and price hinder the majority of consumers to use electro-mobility. A better performance of these attributes requires targeted investments and efficient marketing. Knowledge on the demand and willingness to pay (WTP) for these attributes can help companies adapt mobility products and services to consumer preferences as well as have more targeted investment and efficient marketing.

In this paper, a Discrete Choice Experiment (DCE) is used to estimate marginal WTP for changes of single attributes of mobility products and services related to electric vehicles and other alternatives to conventional vehicles in Germany. The results of this survey identify the drivers and obstacles for the uptake of electro-mobility and can be used to calculate price and cross price elasticities.

The goal of this paper is to use information on consumer preferences for single attributes of mobility. The main research questions are:

- How big is the effect of single attributes of electro-mobility on the WTP and what are specific determinants of WTP values for single attributes?
- What are suitable policy measures to reach target groups in order to increase market shares of BEV and PHEV sustainably?

The results of this market analysis can be used to expand existing business models such as car sharing and joint mobility programs. This enables firms and policy makers to adjust their products, services, and traffic concepts that technological and financial market barriers can be removed.

To close this research gap WTP values using a latent class logit model are estimated. In Sections 3 and 4 the data and explain the method, are described. The estimation results are presented in Section 5 allowing identification of specific user types with higher affinity for products and services for electro-mobility. Section 6 presents a conclusion with a discussion of the results and limitations.

2. Preferences for individual attributes of electric vehicles

Numerous studies and meta studies such as Li et al. (2017) have pointed out significant influence on preferences for alternative vehicles coming from demographic and psychological factors as well as from situational factors such as governmental support, technical features and barriers. Low range and a weak infrastructure are the most important barriers for BEV and other alternative vehicles. Studies investigating efficiency of governmental support are with different results. Though many results indicate positive effects of government support such as subsidies, preferential treatment in traffic, and tax reductions, some measures can be inefficient and require detailed research on additional determinants.

Preferences for alternatives to CV are determined by individual characteristics in different forms. The socio-economic variables age and gender have the strongest impact on the use of car sharing (Carteni et al. 2016). Younger people have a relatively high WTP for new vehicle technologies, in particular for BEV (Cirillo et al. 2017). Some studies indicate significant effects on the WTP also for the number of own cars and own appraisal of expert knowledge (Giansoldati et al. 2018). The estimated price elasticities for the examined technologies vary as well. Consumers who prefer HEV and BV are more elastic than those preferring gas fired engines. Consumers react to price changes for HEV and BEV much more sensitive (Cirillo et al. 2017).

The use of car sharing (CS) can be treated as supplementary option to reduce private car trips. The impact of CS attributes on the intention to substitute the use of CV with CS is important for estimations on the potential of CS to achieve goals of carbon reductions and local reductions of private car use (Liao et al. 2018). Fazel (2014) used the Technology Acceptance Model (TEM) to examine relations between technological characteristics of BEV and acceptance variables. Dudenhoeffer (2013) adopted TEM and found out that personal experience with electric vehicles creates positive effects on the individually perceived usefulness of electric vehicles. Schlueter and Weyer (2019) tested various predictors of acceptance for electric vehicles using the TEM on markets for CS. They found highly mobile individuals living in urban regions motivated to use electric vehicles for car sharing. Moreover, several studies investigate relations between the use of CS on preferences for ownership, on use intensity and gender-related disparities (e.g. Le Vine and Polak, 2017; Kawgan-Kagan, 2020).

In the current study the authors consider CS to estimate marginal WTP for this alternative in order to identify, first, determinants of preferences for CS and, second, potential of CS as an alternative to the purchase of BEV and other non-conventional vehicles. This goes beyond the study of Liao et al. (2017) comparing CS and BEV only.

The attributes travel-costs and travel-time are significant determinants of the preferences for BEV (Carteni et al., 2016). The results of Giansoldati et al. (2018) indicate strong effects of improvements of infrastructure in terms of range, charging-infrastructure, and subsidies on the probability of choosing BEV. The results of other studies such as Bahamonde-Birke and Hanappi (2016) confirm positive impacts of driving range on the WTP and negative effects of fuel and maintenance costs. In addition to general evidence of battery range and distance demanded by consumers, some studies such as Junquera et al. (2016) indicate lower limits of battery range and upper limit of distance. Battery range less than 100 km and distance travelled of more than 200 km will reduce the likelihood of buying a BEV significantly. Detailed knowledge on this limitation of preference structure is important to adjust public support of alternative vehicles and regarded private and public marketing. Even in countries with improvements in the density and quality of charging stations like Denmark and Germany there is still specific need for further improvements in the density and quality of charging stations. Thøgersen and Ebsen (2019) highlight the need for improvements in communication of the status of the changing infrastructure and the plans for its future development as important instruments to reduce consumer uncertainty and problem expectations. Moreover, there is some evidence for lower willingness to pay for BEV and PHEV of women due to lower affinity for charging technologies.

A wide-spread availability of charging stations increases WTP. With regard to policy incentives only investment subsidies increase WTP other policies such as interactions with transit systems, park and ride subscription, and one-year-tickets for public transportation are without effects on the WTP (Bahamonde-Birke and Hanappi 2016).

The share of BEV and PHEV of total market in Germany in 2020 is 4.3% for BEV and 4.8% for PHEV with an overall market share of more than 9.1% compared to around 3.0% in 2019 (FBMV, 2020). In January 2021, around 33,800 normal and 5,600 fast charging points were available in Germany (FNA, 2021). The number of new registered BEV in 2020 was around 358,500. Both, charging points and new registrations of BEV have increased strongly since 2017, i.e. about 10 BEV share one charging point (Association of German Automotive Industry, 2020). While the number of charging stations has increased by a factor of six, the new registered BEV have increased by a factor of 13 in this period. The strongly increasing gap between the market size for BEV and the available charging infrastructure restricts further development of electro-mobility and threatens the master plan charging infrastructure of the federal government despite the fact that Germany has with 382 million Euros the by far biggest public R&D funding for electro-mobility compared to USA (184 million Euros) and Japan (146 million Euros).

3. Data

For new products or at least modifications of existing products not yet introduced, it is impossible to derive demand via observed prices and quantities. As a solution, stated preference methods can be used to ask consumers in questionnaires whether they would –in a hypothetical market setting –buy the new product and what prices they would pay. From a broad set of stated preference methods, DCEs are the most popular in marketing, transportation and energy (Hess and Daly, 2014). DCEs have two key advantages: firstly, the method infers the prices people are willing to pay indirectly by asking people to make trade-offs between various versions of the good rather than asking directly for a WTP. Secondly, it allows the investigation of WTP for several variants of the good at the same time rather than only one specific product configuration. These advantages are especially relevant for our research question, as we can adapt the proposed business models to the preferences of potential car users with respect to BEV variants and various policies support (e.g. free parking for EVs).

The data come from an online survey with a random sample of 405 respondents in Germany. To each respondent 12 choice cards were presented with two mobility options per card with overall 4,860 hypothetical choices. The sample was part of a research project on consumer preferences for sustainable energy and mobility between 2013 and 2017 (Rommel and Sagebiel, 2017). The DCE investigates the WTP for various vehicle types: conventional vehicle (CV), HEV, BEV, electric vehicle with extended range (RE), PHEV and CS. Table 1 shows the different car types and their attributes with one or more different levels. The choice design was developed based on the existing literature and on findings of workshops applying the Delphi method. In a first step 26 theses were presented to a group of six researchers in the field of mobility and business in Germany. The second step includes a follow-up workshop with these experts to discuss different mobility scenarios and expected preference structures.

The above mentioned findings and the expert assessments were used to focus on four alternative types of electric vehicles in comparison to conventional vehicles running with fossil fuels. CS was used as additional alternative to consider possible effects of carbon reductions and local reductions of private car use (Liao et al., 2018). The chosen types of electric vehicles cover available products on the German markets for electric vehicles. We identified five attributes plus the obligatory price attribute. The product specific attributes of each engine type are: power, running costs, driving range, availability of charging stations, bonus, and price. Furthermore, the authors investigate if the demand for BEV would increase with increased availability of charging stations, and additional benefits such as park and ride, free parking in city centers, and usage of dedicated bus lanes.

The first attribute defines the price of the vehicle. Percentage values are used for each type of vehicle with the reference value (100%) of CV. Based on available market data, a range of 80% to 160% is presented[1]. The second attribute describes the power of the vehicle. CV is also used as reference value of 100% and all other types of vehicles have levels between 80% and 120%. The third attribute defines costs for fuel and maintenance in Eurocents per kilometer. The fourth attribute presents a bonus for buying or using vehicles with alternative engines. The fifth attribute considers the range of the vehicle in kilometers. To consider different levels of available charging stations, the last attribute describes the availability of charging stations as nominal scaled variable. Table 2 exemplifies one out of 12 choice tasks, respondents were confronted with.

[1] We decided to use 100% as reference value related to the individual price perception instead of prices in Euros to avoid uncertainties of respondents about the real price.

4. Method

In our theoretical model of choice, we assume that total utility of a vehicle is the sum of the utilities from each attribute plus a constant utility for the vehicle type. For example, the utility for a BEV can be written as:

$$U_{BEV} = \beta_{BEV} + \beta_1 Price + \beta_2 Power + \beta_3 RunCost + \beta_4 ParkRide + \beta_5 FreePark + \beta_6 BusLane + \beta_7 Range + \beta_8 Avail \quad (1)$$

where U_{BEV} represents utility a respondent receives from this specific configuration of the BEV. β_{BEV} represents the utility increase or decrease of a BEV in its base configuration compared to no car, and the remaining β parameters represent the utility derived from the attributes. For each vehicle type presented in the choice set, the respondent chooses the vehicle type that provides the highest level of utility. To increase the number of observations, each respondent was asked to make this choice twelve times with different values of the attributes.

To analyze the data, discrete choice regression models can be used (McFadden, 1974). The choice made by the respondents serves as the dependent variable and the type of car and the attribute levels are the independent variables, used to explain the choice. To model choice probabilities, the logit model is used which in its most simple case as a conditional logit model gives the following formulation.

$$Prob(chooseBEV) = exp(U_{BEV}) / \sum(\exp(U_i)) \quad (2)$$

where $i = (CV, HEV, BEV, RE, CS, NC)$ is an index for the different car types.

The β parameters can be estimated with the maximum likelihood method. The estimated parameters can be then transformed into WTP values by dividing the parameters for the non-cost attributes and vehicle type by the parameter of the cost attribute. The WTP is the marginal rate of substitution between the attributes and the additional costs, and reflects the maximum amount a respondent is willing to pay for a one-unit increase in an attribute. As it can be expected that different people have different preferences (the assumption in the conditional logit model is homogenous preferences), the model is extended to a latent class logit model. In this version, preferences for different preference classes can be estimated, each class being endogenously determined, and consisting of a separate set of β parameters. In this paper, results from a two-class model are presented.[2] The standard latent class model was used to analyze group heterogeneity for the study sample.

In the final version of the questionnaire, each respondent answered 12 choice sets, which were generated from a Bayesian efficient design, minimizing the standard errors of the β parameters for a conditional logit model (Rose and Bliemer, 2008). The design was created with

[2] For the sake of brevity, the authors will not explain the statistical model and estimation procedure in detail. We refer the reader to Truong, Hensher (2014) for a general explanation of DCEs and estimation and to Sagebiel (2017) for a more detailed description of the latent class model.

Table 1
Attributes and vehicle types.

Attribute	CV	HEV	BEV	RE	PHEV	CS
Price in % of reference level	100	80 100 120 140	120 140 160	120 140 160	80 100 120 140	120 140 160
Power in % of reference level	100	80 100 120	80 100 120	80 100 120	80 100 120	80 100 120
Running costs (€ct/km)	1 13 16	1 13 16	8 11 14	8 11 14	8 11 14	1 13 16
Bonus	No	no	No Park&Ride Free parking city center Usage of bus lane	No Park&Ride Free parking city center Usage of bus lane	No Park&Ride Free parking city center Usage of bus lane	No Park&Ride Free parking city center Usage of bus lane
Range (km)	700	700	150 200 240	200 300 400	700	350 450 550
Availability of petrol/ char-ging stations	High	high	Low medium	Low medium	high	Medium High

Table 2
Choice Set example.

	CV	HEV	BEV	RE	PHEV	CS	No
Price in % of reference level	100%	100%	140%	160%	100%	160%	
Power in % of reference level	100%	100%	100%	100%	100%	100%	
Running costs (€ct/km)	13 ct/km	16 ct/km	14 ct/km	14 ct/km	8 ct/km	16 ct/km	
Bonus	No Bonus	No Bonus	Usage of bus lane	Park & Ride	Free Ⓟ in city center	No Bonus	
Range (km)	700 km	700 km	200 km	300 km	700 km	450 km	
Availability of petrol/charging stations	high	high	low	low	high	medium	
I choose…	☐	☐	☐	☐	☐	☐	☐

the software NGENE (ChoiceMetrics, 2018). Prior values[3] for the parameters, which are necessary to create the design, were taken from results of a pre-test with 100 respondents. The design for the pretest was similarly generated, yet with priors derived from the literature review and the expert interviews from the Delphi method.

5. Results

The chosen vehicle types, independent of the attributes and their levels are analyzed. Respondents have infrequently chosen BEV what is in line with vehicle purchases in Germany (FBMV, 2019). About 40% of the choices fell into conventional vehicles. This means that more than half of the choices made were against any kind of BEV. From the 45% of choices of BEV, Plug-in hybrid vehicles made up half (20%). These stated preferences differ from vehicle purchases in Germany in 2019 (FBMV, 2019). Car sharing does not seem to be an attractive alternative to the respondents.

5.1. Results of the latent class model

To investigate the impact of the attributes on choice, a latent class logit model is estimated with two preference classes. Parameters for each vehicle type (alternative specific constants, ASC) as well as for all attributes (see Section 3.1) are estimated. Furthermore, a parameter that represents the class probability as well as parameters for socio-demographic variables that explain the class probability is estimated. These variables were gender, age, household income, and whether the respondents live in their own or a rented house (*rent*) and selected based on the findings of previous studies (see Section 2). The model was estimated using the software package Stata with the user written command *lclogit2* (Pacifico and Yoo 2013)[4]. Table 3 shows the estimation results, columns representing the classes and rows representing estimated parameters. The percentage values in the first row represent the sizes of the classes.

The first class has a slightly higher share than class 2 with 63%, i.e. it is more likely that a randomly selected respondent falls into class 1. This class membership probability is partly influenced by the socio-demographic variables. While gender and income do not have a statistically significant impact on class membership, age and rent do. Younger respondents and those who have rented an apartment are more likely to be member of class 1.

For example, an 18 year old female, who has rented an apartment, has a probability of 75% to be member of class 1, while a 65 year old male, living in his own house has a probability of only 52% to be a member in class 1. Especially house ownership status makes a large difference. A person renting a house has a probability of about 10 percentage points more than a person who owns a house.

Comparing the estimated parameters between classes, it quickly becomes obvious that preferences in the two classes differ, i.e. preference heterogeneity is present due to differences in covariates between the classes. Class 1 shows stronger preferences for BEV and RE, while in class 2, the people tend to opt for conventional vehicles and car sharing, with no interest in BEV and RE. Thus, the main distinguishing factor between the two classes is the acceptance of BEV.

With respect to the attributes, preferences vary between classes mainly in magnitude and significance, but not in direction. In both classes, people prefer lower purchasing prices and running costs, and are indifferent towards power. However, class 1 has significant and positive parameters for availability of petrol stations and range, while these parameters are not significantly different from zero in class 2.

[3] Priors are the a-priori expected coefficient values. In an efficient design for nonlinear models, these are required to minimize the determinant of the variance–covariance matrix, which is the ultimate goal of such design strategies.

[4] The authors have estimated several competing models, which are available on request. The model presented here appears to be the best model in terms of model fit and plausibility.

Table 3
Results Latent Class Model.

	Class 1 (63%)	Class 2 (37%)
Alternative specific constants (Standard errors in parentheses)		
Conventional vehicle (CV)	3,124***	6,200***
	(5.19)	(4.64)
Hybrid (HEV)	3.273***	3.814***
	(5.42)	(2.75)
Electric vehicle (BEV)	3.886***	1.420
	(12.12)	(1.58)
Range Extender (RE)	3.249***	−0.0933
	(8.65)	(-0.08)
Plug-in-Hybrid (PHEV)	3.415***	2.849**
	(5.61)	(2.05)
Car Sharing (CS)	2.390***	4.332***
	(4.61)	(3.96)
Attributes		
Price (change to conventional in %)	−2.139***	−1.190***
	(-16.75)	(-3.09)
Power (in %)	−0.131	−0.131
	(−0.90)	(−0.35)
Usage costs	−0.219***	−0.102***
	(−23.41)	(−5.38)
Boni: Park & Ride	−0.316***	−1.037***
	(−3.13)	(−3.60)
Boni: Free parking	0.118	−0.422
	(1.19)	(−1.63)
Boni: Usage of bus lanes	−0.218**	−0.496*
	(−2.18)	(−1.95)
Range	0.192***	−0.135
	(2.91)	(−1.13)
Availability of petrol stations	0.292***	−0.0252
	(2.95)	(−0,.1)
Covariates class probability		
Gender	−0.0856	
	(−0.40)	
Age	−0.0141**	
	(−2.32)	
Rent	0.439*	
	(1.90)	
Income	−0.0164	
	(−0.54)	
Constant	1.166**	
	(2.51)	
Observations	4860	
Respondents	405	
BIC	13,336	
AIC	13,204	
Log Likelihood (Null)	−9,457	
Log Likelihood	−6,569	

t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

This finding mirrors that class 2 members are not interested in BEV. If a respondent does not consider buying a BEV or RE, range and availability of petrol stations do not matter. The parameters regarding the bonus attribute provide a rather ambiguous picture. There is a negative preference for Park & Ride and Bus Lane and no significant effect of free parking spaces. The negative effect could be due to some respondents not agreeing with policies that give privileged rights to BEV. Overall, the results indicate that:

1. Most results of the preference analysis are reliable for class 1. All vehicle types indicate preferences on the one percent significance level. Most of the attributes, except power and free parking bonus determine the WTP significantly.
2. The results of the LC model for class 2 indicate preferences on the one percent significance level only for CV and CS.
3. Preferences for BEV are lower than expected based on findings in literature.
4. Non-financial support is with low or negative effects.
5. Lower prices are still the most convincing argument to buy a BEV.
6. Younger people and tenants are more likely to opt for alternative vehicles.

5.2. Discussion of the willingness to pay

To use the statistically valid results in the development of business models, the estimated parameters are transformed into WTP values. These values can be directly integrated into a cost-benefit analysis and can be used by entrepreneurs to develop a business plan specifically dedicated to the preference structure of consumers. Additionally, WTP values provide useful information to policy makers who consider subsidizing BEV.

WTP values are expressed in terms of percentage costs to the reference costs, i.e. the costs people would pay for a conventional vehicle. These values explain which percent people are additionally willing to pay for a one-unit improvement of an attribute. In Table 4, WTP of significant attributes and their confidence intervals calculated with the Krinsky and Robb method are reported (Krinsky and Robb, 1986, 1991), using the Stata command *wtp* (Hole, 2007).

WTP for usage costs is 10.2% and 8.6% for classes 1 and 2, respectively. This means for a decrease in usage costs by one Eurocent per kilometer, people are willing to pay between 10% and 8% more for purchasing.[5] The effects of range and availability of petrol stations are significantly different from zero only in class 1. For an increase in range by 100 km, people in class 1 are willing to pay 9% more and for a high availability of petrol stations, the additional WTP amounts to even 27%. This shows that people require better BEV infrastructure. Yet, if this infrastructure is present, BEVs and PHEVs are a realistic option and people are willing to pay extra. Finally, the introduction of Boni has no or negative effects. If bus lanes are dedicated to BEV, WTP goes down by 10% for class 1 and 42% for class 2 and park and ride options lead to a lower WTP of 14% for class 1 and nearly 90% for class 2. This emphasizes the argument that people are not in favor of privileges for BEV especially those people who are generally not interested in ownership.

The study of Junquera et al. (2016: 12) confirms the attributes price perception and charging times as main determinants of the WTP for BEV. The results are also in line with the findings of Bahamonde-Birke and Hanappi (2016). They find a strong impact of usage costs and charging infrastructure on the willingness to pay as well as low effects of supporting policies such as park and ride subscriptions. Regarding the effect of age on the WTP for BEV the findings of this study are confirmed by the study of Cirillo et al. (2017). They found that younger people place relatively high WTP for new vehicle technologies, in particular for BEV.

Aggregating the results shows that especially in class 2 many people are still not ready to buy BEV. Furthermore, incentivizing the purchase through privileged usage rights will not lead to a larger share of BEV. More important are the range and the availability of petrol stations and require technological advances and investments into infrastructure.

To get a clearer picture of the demand for BEV, price elasticities of demand and cross-price elasticities for investment costs and maintenance costs are calculated. The price elasticity for investment costs in case of HEV in class 1 is very elastic, i.e. increasing investment costs by 1% increase the probability of reduced demand by 2.74%. In contrast, members of class 2 react inelastic or with low elasticities, therefore only elasticity values of class 1 are illustrated in Table 5. The price elasticity for BEV is very high (-3.12) in class 1. The price elasticities for RE and CS are also very high. Similarly, demand for PHEV is very price elastic (-2.65) in class 1.

Cross-price elasticities for all alternative vehicles (without CV) are very low in both classes. A comparison of elasticity values for changes

[5] With an assumed total mileage of around 200,000 km the savings in usage costs are 2,000 Euros, and the expected savings of an average purchase price of 30,000 Euros is then between 2,400 and 3,000 Euros.

Table 4
WTP in Percent for significant attributes.

	Class 1	Class 2
Usage costs	−10.2 [−11.9;-8.9]	−8.6 [−25.5;−4.0]
Boni: Park & Ride	−14.8 [−24.2;−5.7]	−87.2 [−203.5;−39.0]
Boni: Usage of bus lanes	−10.2 [−18.8;−1.9]	−41.7 [−107.3;−2.5]
Range	9.0 [3.1;15.9]	n. s.
Availability of petrol stations (Low → High)	27.4 [10.0;47.0]	n. s.

Notes: Confidence intervals in brackets are calculated with the Krisky and Robb method. n.s. means attribute is not significant.

	Class 1	Class 2
Usage costs	−10.2 [−11.9;−8.9]	−8.6 [−25.5;−4.0]
Boni: Park & Ride	−14.8 [−24.2;−5.7]	−87.2 [−203.5;−39.0]
Boni: Usage of bus lanes	−10.2 [−18,8;−1,9]	−41.7 [−107,3;−2,5]
Range	9.0 [3.1;15.9]	n. s.
Availability of petrol stations (Low → High)	27.4 [10.0;47.0]	n. s.

Notes: Confidence intervals in brackets are calculated with the Krisky and Robb method. n.s. means attribute is not significant.

Table 5
Price elasticities of demand in class 1.

Vehicle type	Price elasticity
HEV	−2.741
BEV	−3.116
RE	−3.134
PHEV	−2.654
CS	−3.148

in fuel costs shows differences between classes 1 and 2 and between vehicle types. Members of class 1 react more sensitively to changes in fuel costs. The values of cross-price elasticity are very low for all alternative types of vehicles in both classes. Generally, the results of the elasticity analysis indicate very sensitive consumer behavior for changes in fuel costs for members of both classes. For changes in prices only members of class 1 react sensitive. Cross-price elasticities are low in both classes.

6. Discussion and conclusion

6.1. Discussion of results

As shown in chapter 2 the number of charging points has risen half as much compared to the number of BEV and PHEV since 2017. Therefore, the availability of charging points is increasingly a scarce resource. Distinct availability of charging stations has high priority for consumers as illustrated in the results of our DCE. The strong growth of BEV and PHEV in Germany since 2017 is without adequate capability of the charging infrastructure due to the uneven growth of the charging infrastructure and of the market size for BEV and PHEV. Consequently, the bottleneck of the market development for BEV and PHEV is still the gap between the high priority of available charging points as illustrated in the results of the DCE and the slow growth of vehicles per charging point in average.

The range of BEV on the German market has increased by around 8 percent since 2016 (e-zoomed, 2020) what could be seen as low compared to the considerable progress in battery technology during the last years, for two reasons. Firstly, the majority of new registered BEV has a range of 200 to 400 km. This reduces the average range because the group of BEV with a range of more than 400 km has become smaller since 2016. Secondly, the formerly used standard measurement for range was the New European Driving Cycle (NEDC). Due to inaccuracies it was substituted by the more Worldwide Harmonized Light Vehicle Test Procedures (WLTP). For PHEV the situation is approximately the same, but on a lower level due to a lower number of new registrations per annum (e-zoomed, 2020). Consequently, also the market supply for the second attribute with a high WTP illustrated in the DCE does not meet the demand.

The results of the DCE and their effects of prospective business models illustrate a great need to communicate various advantages of improvements in the market segment grid infrastructure for electromobility to specific demographic groups. The levy of additional WTP requires, firstly, intelligent business models capable to increase market shares of BEV and other alternative vehicles and mobility services with transparent measures to invest in the preferred attributes. Secondly, since 2019 the electric vehicle bonus granted by the German Ministry for Economics is 6,000 Euro for BEV based on the net list price up to 40,000 Euro and 5,000 Euro up to a net list price of more than 40,000 Euro. The bonus for PHEV is 4,500 respectively 3,750 Euro. Since November 2020 an additional bonus is paid due to COVID19 aid-programs (BAFA, 2020). This financial support has shifted the demand curve for BEV and PHEV upwards. The growing market size corresponds to the goal formulated in the master plan charging infrastructure of the federal government but at the same time increases the gap between the high priority of available charging points and range on one hand and the number of BEV and PHEV on the other. Suppliers of mobility solutions should identify the preference structures for the identified target groups more detailed in order to absorb the WTP for improvements in the charging infrastructure.

The results of the DCE give only first insights into the preference structures for alternative concepts of mobility. If the results can be replicated by further research, reductions of purchase costs and running costs are essential to improve the competitiveness of BEV and other alternative vehicles which are currently not competitive. Different boni for the use of BEV such as park & ride, free parking, and the usage of bus lanes are not attractive for consumers which corresponds to the findings of Bahamonde-Birke and Hanappi (2016). The results of the latent class model indicate options for specific measures for innovative consumers. Based on general preferences for range, improved charging-infrastructure, and reduced running costs outstanding WTP values of young tenants can be activated with specified marketing activities. Consequently, there are several lessons learned: Firstly, the market efficiency of publicly financed bonuses as used in Germany is limited as long as the heterogeneous preferences for attributes of BEV and PHEV are not fully taken into account. The results of the DCE indicate additional WTP for improvements of the charging infrastructure for young urban tenants. Particularly, in urban areas investments in the charging infrastructure will benefit from scale effects due to lower fix costs compared to sub-urban and rural areas with lower demand and higher travel distances. Secondly, for the attribute range consumer´s desires can be met less costly in urban areas due to the growing demand for BEV with a range between 200 and 400 km (e-zoomed, 2020). Thirdly, investments for improvements in available technology are required to reduce charging time. Charging times comparable to times needed for filling up petrol or diesel vehicles will lead to a substantial improvement of the charging infrastructure. Recent developments of charging stations have shown charging times of 10 min. for 25,000 $ BEV will become marketable (Yang et al., 2021).

Moreover, due to the unbalanced relation between the charging infrastructure and strong drivers of preferences for BEV and PHEV, more investments of the transportation industry in urban charging points and reductions of charging time in co-operation with municipalities will be capable to solve this problem (Nicholas and Wappelhorst, 2020). The remaining gap between the growth rate of BEV and PHEV and the improvements in charging infrastructure in Germany indicates that the transferability of the study results is not fully given. However, the comparison of the status of e-mobility in Germany with some other countries as shown in section 1 indicates high transferability in terms of cost reductions. But this success of financial bonus for purchasing BEV and PHEV creates the follow-up problem that the charging infrastructure cannot keep up.

6.2. Limitations

It is important to note that the results of the DCE are limited for various reasons. First, the results are based on hypothetical markets and can be used only as indications of market trends. Second, technical constraints on the supply-side and regulations of public authorities are not considered in the DCE. In light of the transportation policy goals of the German Federal Government, the Bundeslaender, and many municipalities, market introduction of technical solutions and intensity of policy support play a crucial role for the development of markets for electro-mobility. These measures can be drivers or obstacles for demand-side activities. Currently the buyer´s premium for BEV and PHEV paid by the federal government are regardless of individual preference structures such as of tenants and young females (Kawgan-Kagan, 2020). More consideration of supply-side measures on markets for electro-mobility will intensify changing mobility behavior. Despite the limitations of the DCE, it is clear that investments in electro-mobility should concentrate on the preferred attributes with specified marketing for the defined target groups. To confirm the reliability and validity of the estimated stated preferences with revealed preferences, further research and in particular market simulations and field experiments are required in order to increase efficiency of current market incentives for BEV and PHEV purchases in Germany.

CRediT authorship contribution statement

Kai Rommel: Conceptualization, Resources, Investigation, Validation, Writing - original draft, Visualization, Project administration. **Julian Sagebiel:** Methodology, Investigation, Software, Formal analysis, Data curation, Validation.

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