Technical University of Munich

TUM School of Management

Master Thesis:

Exploring the Behavior of Electric Vehicle Drivers and Their Decision-Making with Respect to Usage of Public Charging Infrastructure.

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I want to express my deepest gratitude to my beloved wife, who encouraged me to do my MBA and supported me on the whole way, to my parents and son and to all teachers of the TUM School of Management. I am also especially grateful to Prof. Dr. Schwenen for fruitful exchange in ideas and constant support in my master thesis.

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Table of Abbreviations

EV…. electric vehicle

EMP...e-mobility service provider

POI… point of interest

V2G…vehicle to grid

1. Introduction

1.1 Context

The electric mobility is fast developing in different markets including Europe, USA, and especially China. The electric powertrain technology is disrupting the industry as it is considered a clean technology that can potentially bring economic and environmental benefits to all the stakeholders. Electric driven cars gain more and more acceptance among users[1] because of higher efficiency, powerful acceleration, and low noise pollution.

CO_2 emissions that contribute to global warming are especially important aspect in this context. Researchers agree that electric vehicles when used with regenerative electricity can be a solution to reduce dependence on fossil fuels and as a result decrease the CO_2 footprint (Element Energy, 2013). Hence, European Union invests in policy measures supporting increased penetration of electric cars (subsidy schemes, tax incentives, etc.). In this regard, German government set a target to reach one million electric vehicles by 2020. As it can be seen in Figure 1 the sales of electric vehicles increased in 2018 by 34% in Europe, by 78% in China and by 79% in the United States of America.

[1] In this master thesis when I speak about users, I mean drivers of cars as there is a major trend in the mobility from property-oriented business models to on demand mobility, so the driver is not necessarily the owner of the car.

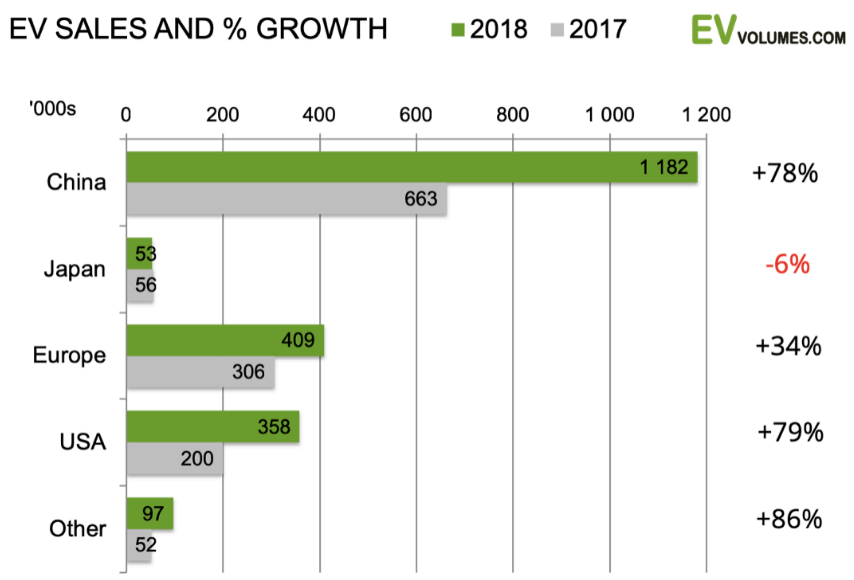


Figure 1. EVs sales in 2017 and 2018. (EVvolumes, 2019).

Moreover, effective use of renewable energy can further decrease dependence on fossil fuels and CO_2 footprint. Scheduling electric vehicles (EVs) charging to times when significant amount of energy is generated from sources like sun or wind can help to stabilize the grid (Neves, Marques & Fuinhas, 2018). In addition, there is a need for intermediate storage of the energy as energy production from wind and solar is highly dependent on the weather. In context of increasing power of renewable energy sources, the battery capacity of electric vehicles could be used for intermediate storage of energy (Flammini et al., 2019). These aspects are at the moment in the focus of researches and industry when it comes to new business models.

1.2 Contribution

Although looking at the current growth rate one might say that the tipping point for electric mobility is approaching in important markets, however, there are still some challenges on the way to high penetration of electric vehicles. Researchers, governments, and industry representatives agree on the fact that one of the biggest challenges of the electric mobility is the lack of public charging infrastructure (Otto, Sponring & Freier, 2018). Currently and in the nearest future this challenge will remain a key step required to increase the number of EVs as the range of electric vehicles is not high enough and frequent charging is needed.

But which factors are important for the growth of charging infrastructure? From the interviews with operators of public infrastructure I know that the utilization and profitability of public infrastructure are very low at the moment. On the other hand, there are numerous studies that investigate the impact of peaks on the sustainability of the grid. Such system peaks can be a big threat for the grid and even cause blackouts and increase the costs for operators of public charging infrastructure (Marmaras, Xydas & Cipcigan, 2017). By distributing cars more efficiently between charging stations higher utilization with lower number of charging stations can be achieved. Higher utilization would also help to cut the investments in charging infrastructure as fewer charging stations would be needed. This will reduce the peaks in the grid and increase the profitability.

Several studies examined the topic of factors which can incentivize a changing in behavior of users in mobility context. For example, Mortimer et al. (2018) demonstrate that smart financial incentives can improve driving behavior. Angelopoulos et al. (2018) show that users can be incentivized to relocate the cars by financial incentives in the context of car-sharing. Following the suggestions in the above-mentioned studies, I assume that one way to distribute cars optimally between charging stations is by incentivizing users of electric vehicles to make a detour and deviate from their predefined route. In this master thesis, I investigate the drivers' decisions to make a detour, as well as the incentives which can motivate drivers to make a detour.

The main hypothesis of this master thesis: monetary incentives can affect the decisions of the electric vehicle's users in context of public charging.

1.3 Situation analysis with respect to business models

In this master thesis I am going to apply the findings regarding charging habits of electric vehicle drivers on business models and suggest new ways that can enable faster growth of public charging infrastructure. For this purpose, target market and audience should be defined.

The majority of the charging events today take place at home or at work. This is because most early adopters of electric vehicles live in single-family homes with a possibility to install a charging station in their garage. In contrast my focus lies on public charging infrastructure because the demand for it will further increase in the future as the number of people interested in buying an electric vehicle who live in the cities and do not have a charging possibility at home will rise. At the same time the number of people residing in the cities is increasing with the urbanization trend. From the expert interviews I know, that the share of charging events at public charging stations should increase from 20% nowadays to 40% (30% city, 10% highway) by 2030.

Users that live in cities and reside in multi-apartment buildings could also become one of the key target audiences for the future of EVs as driving diesel and petrol cars may be forbidden (this process has already started in Germany in Austria) in urban areas. Further on, due to usually short driven distances around the city EVs represent a perfect fit for city drivers. However, as mentioned earlier, the speed of EVs adoption by this category of drivers is highly dependent on availability and development of EV public charging infrastructure.

The shares of public charging stations on all charging stations given in Table 1 (Charge Map, 2019) confirm the mentioned above current usage of public charging infrastructure. The shares of charging stations on the highways, public streets, shops and parking places sum up to 40%.

Place	Share
Highway	1,4%
Public street	12,8%
Shop	7,7%
Parking	25,8%
Sum	45%

Table 1. Charging infrastructure. (ChargeMap, 2019).

Results of my survey show that 43% of electric vehicle users charge their cars at least once a week or more at public charging infrastructure. Additional 22% use public charging stations 2-3 times a month. Similar results were observed in context of semipublic charging infrastructure, for example at a parking place of a supermarket or department store.

As it can be seen from Table 2 charging events last much longer than refueling of the petrol car which can lead to a different user behavioral pattern during the charge compared to refuel. The time spent at the charging station should be meaningful for the driver. This can be realized if the charging event happens supplementary to some other activity like shopping or coffee pause. Therefore, in the context of the new business model I am going to consider points of interests (e.g. coffee, restaurant, supermarket and others) located near to charging stations.

Maximum power	<11kW	50 kW	150 kW	350 kW
Avg. time for charge @100kWh (~400 km range)	>10 h	~ 2 h	~ 45 min	~ 25 min
Share in Germany and Austria	60%	30%	8%	2%

Table 2. Public charging infrastructure (Chargemap, 2018).

According to the above-mentioned there is a space for new business models on the intersection of charging stations and points of interests. In contrast to gasoline stations for combustion engine powered cars, charging stations for electric cars are more dispersed, their availability is smaller, and charging takes longer. Hence, matching supply and demand such that e-car drivers obtain high service at low prices and increase the profitability of charging station operators through increased utilization of infrastructure is a formidable planning task. I am using survey data to suggest new business models to charging station operators and points of interest near charging stations. Analyzing the survey data, I aim to identify strategies to increase utilization of currently available charging stations and offer value added to the drivers of electric vehicles. This thesis is built as follows: in the following section a review of relevant literature is provided, followed by description of the data and methodology. Analysis of the EV drivers' behavior is given in sections 4 and 5. Section 6 elaborates on new business models that can be built using the results of my research. Section 7 concludes.

2. Literature Review.

While the whole topic of electric cars is rather novel, still there are several theoretical studies with models describing demand for services (for example refueling cars) in a network (Hodgson, 1990; Hakimi, 1964) which can also be relevant at least to some extent in the context of my research question. These models assume that the highest demand for a service will be observed at the knots of the network, for example close to home or at work in the case of vehicle or at the links - on the way from origin to destination.

Although the empirical literature on the refueling preferences of electric vehicle users is rather scarce, there are some studies (Philipsen et al, 2018) that find similarities in refueling habits of EV drivers and conventional car drivers. Based on revealed-preference survey data on 1.021 drivers in Germany, Philipsen et al. suggest that there is no difference between the two groups regarding range-relevant factors. Based on their study the filling level which is perceived as critical is identical for fuel tanks and batteries. This study also states that in terms of behavioral patterns, electric vehicle users tend to charge consumed quantities as soon as they have a possibility, while users of vehicles with combustion engines often refill the tank completely.

Further on, Kelleyand and Kuby (2013) investigated driver's willingness to deviate from their route in order to refuel their car. The study is based on the survey of 259 drivers of compressed natural gas (CNG) vehicles in Southern California. They found that ten times more drivers preferred to refuel at the stations on their way between their origin and destination than at the stations closer to their home.

Even less investigated is the context of factors that have an impact on decisions of electric vehicle drivers with respect to charging at public charging infrastructure. Ensslen et al. (2018) created and analyzed a load-shift-incentivizing electricity tariff that is suitable for electric vehicle users. The tariff was analyzed via surveys in German and French electricity markets and acceptance by electric vehicle users and fleet managers of controlled charging was investigated. The aim of the tariff and controlled charging was to decrease the charging managers' expenditures. The charging managers are expected to guarantee for a complete recharge at the end of the charging event if time for recharging is sufficient. Between the time of achieving minimum range required by electric vehicle driver and the end of the charging event, the charging managers can use the remaining degrees of freedom to control the load and time of the charging process, if parking times exceed minimum charging times. In contrast to my work this paper focuses on tariff for households and organizations.

Daina, Sivakumar and Polak (2017) created a model that captures the behavioral nuances of tactical charging choices in smart grid context, using empirically estimated charging preferences. The paper provides insights into the value placed by individuals on the attributes of the charging choice like duration of charge, the charging cost and the amount of energy available in the battery after charging. The authors focus on the impact of such technologies like load-shifting applied, for example at home or work chargers, that can manage the power of charging stations in order to reduce the peaks in the grid.

Franke and Krems (2013) analyzed the charging behavior of drivers in a German EV trial and found evidence that among other factors range level affects charging decisions. Helmus and Van Den Hoed (2015) examine the particular charging patterns of different user types in terms of timing, charging amount and location preferences. They combined the specific user patterns with probabilities on which locations these users are likely to charge and created predictions how charging points are likely to be used, as well tools for policy makers to make strategic decisions how to optimize the roll out of new charging infrastructure.

Sun, Yamamoto and Morikawa (2016) explore in their study how battery electric vehicle users choose where to fast-charge their vehicles from a set of charging stations, as well as the distance by which they are generally willing to detour for fast-charging. The study is based on the panel data from a two-year field trial on battery electric vehicle usage in Kanagawa Prefecture, Japan. The key findings are that private users traveling on working days show a strong preference for free charging. Commercial users are ready to pay for charging at a station in order to avoid a big detour.

Flammini et al. (2019) used a real dataset of 400.000 electric vehicle charging transactions from Netherlands in order to analyze the key figures such as charge time, idle time, connected time, power, and energy. The aim of the paper is to represent the multi-modal probability distributions of the relevant variables and the discussion based on provided information regarding possible deployment of V2G (Vehicle to Grid) solutions. The worldwide EVs demand in 2015 accounts to 3,3 GWh. At the same time the penetration is very low and sum up to 3 EVs for every 1000 vehicles. Flammini et al. (2019) found that 25% of the total energy is supplied in the weekend, and the mean energy supplied to each EV is 8,5 kWh per transaction. Further results are following: 50% of the recharges last for less than 4 h; the idle time depends on the geographical location of the charging station, and on average it lasts also for 4 h. The paper suggests handling the demand through appropriate communication before the EV arrival, for example, through a smart application.

To the best of my knowledge there are no studies published which describe the behavioral aspects of electric vehicle drivers with respect to pricing and incentives in form of discounts for an offer at a charging station in Germany and Austria so far. In this master thesis, I aim to fill in this gap and to investigate the possibilities to reduce potential peaks in the grid and to increase the utilization of public charging infrastructure by providing incentives to the drivers of electric vehicles.

3. Methodology

3.1 Interviews with experts

In order to better understand the current situation, I conducted several unstructured interviews with experts from automotive industry, charging station operators, energy companies, and representatives of points of interests. The aim of this research was to identify current problems in the field of charging stations and to make predictions for future developments. During the interviews I also discussed different business models in order to get some feedback from the experts.

3.2 Data collection via survey

The data for this thesis was collected via an online survey in autumn 2018. It was important for the goal of my master thesis to include only electric vehicle drivers and not plug-in hybrid drivers or drivers of conventional vehicles in this study. In order to achieve this goal, a news feed about electric vehicles in "Facebook" was created. The followers of this news feed were later invited to take part in the survey. In total the data on 186 electric vehicles drivers was collected.

The survey included a part of general socio-demographic questions revealing such characteristics as gender, age, country of residence. Further on, some questions about the charging preferences and currently driven by the respondent model of the electric vehicle were asked. The respondents were also asked about their opinion regarding current problems of public charging infrastructure.

Further major part of the survey was a so-called choice experiment. In this part the respondents were asked to choose whether they would make a detour to charge their car in a specific setting or not. For the choice experiment a set of factors – discount on electricity price, goods/ services or different power level - was included. The whole survey can be found in Appendix.

In the end of the survey respondents were asked which app for the search of a charging station they are currently using. In order to support the brainstorming process for new business models and app functions respondents were asked about disadvantages of the apps they are using now. The respondents were also asked to rate some innovative functions of the app they would use and propose their own ideas.

The process of data collection of this survey was executed in cooperation with M. v. Klot, a student at TU Munich. Further on, a special mobile application to observe actual charging behavior of electric vehicle drivers was created. The promotion of this app to collect enough data to make a solid research is beyond the scope of this master thesis. However, the collected in the app data on the 5 electric vehicle drivers can serve as a good supporting tool to my main research. In the following section, the choice experiment is described in detail.

3.3 Choice experiment

There were three main sections of questions in the choice experiment which covered the main tested in this thesis incentives to increase the probability of detour by EV drivers: discount on the energy price at charging station, discount on goods at the charging station and different power levels on charging station.

First section: questions regarding detour of 10 minutes in exchange for a discount on a product or service at charging stations including additional question regarding free coffee.

Example:

"Imagine you have to charge your car and you are searching for a charging station. Would you take a 10-minute detour to get 10% off a $ 20 purchase while shopping?"

Second section: questions regarding detour of 10 minutes in exchange for a discount on energy.

Example:

"Imagine you have to charge your car and you are searching for a charging station. You have the option for a more distant charging station to get a discount worth 2 € on charging. Would you take 10 minutes detour for this discount?"

Questions in the first and second sections offer a detour of ten minutes in exchange for a discount either on energy or on the goods or services offered at the respective charging station. These questions with different values of discounts were asked several times to test the willingness to accept a detour. The discount on purchase near the charging station was equal to 10%, 25%, and 50% discount. There were also three questions regarding discount on the energy with the same financial gain, but given in absolute values of 2€, 5€, and 10€ respectively.

Third section: questions regarding different power level of a charging station.

Example: “Would you take a detour of 10 minutes to reach the charging station with 22 kW instead of the charging station with 11 kW?”

A combination of questions investigating the same incentive is called a choice set.

3.4 Research Methodology

In order to answer my research question, I use conditional logistic regression, a specific version of logistic regression that is frequently used to analyze discrete-choice experiments especially in the transport choice context. The conditional logit model introduced by McFadden in 1973 is similar to the logistic regression (XLStat, 2019). However, the key idea behind this model is that the choice among alternatives is treated as a function of the characteristics of the alternatives, rather than (or in addition to) the characteristics of the individual making the choice. In this regard the model fits well my research interest in this thesis, which is to investigate the specific factors to increase the probability of EV drivers making a detour.

Another specifics of conditional logit model is that instead of having one line per individual like in the classical logit model, there will be one row for each category of the variable of interest, per individual (XLStat, 2019), so each choice in each of the asked questions is treated as a separate observation. In the case of my research, drivers of electric vehicles were asked to decide between two alternatives in each choice set: the base alternative was not to do a detour and not to gain an incentive. Another alternative was to take a detour and get a monetary gain or reach a charging station with higher power. I group the questions on the same factors in choice sets. As a result, I have three choice sets that are analyzed in separate regressions and provide insights of the impact of discount on energy price, discounts on offered goods or services, and power level of the charging station on the choice of EV driver to make a detour.

The general model, which I estimate using statistical software STATA, is written as

$$\eta_{ij}=x'_i\beta_j+z'_{ij}\gamma$$

where η_{ij} is the *j*-s choice utility of user *i* which depends on characteristics of the individuals as well as attributes of the choices; x_i represents characteristics of the individuals that are constant across choices, and z_{ij} represents characteristics that vary across choices; $\boldsymbol{\beta}_j$ is the estimated regression coefficient which is interpreted as reflecting the effects of the covariates on the odds of making a given choice.

4. Descriptive statistics

In this section, some descriptive statistics and the first results of the survey are presented.

4.1 Main socio-demographic characteristics of EV drivers

The focus of my survey lies on German and Austrian market. As it can be seen from Figure 2 the respondents from these two countries represent the majority of the sample namely 61% and 27% respectively. Although some responses from other countries including for example USA, Switzerland, and Netherlands are also present in the sample.

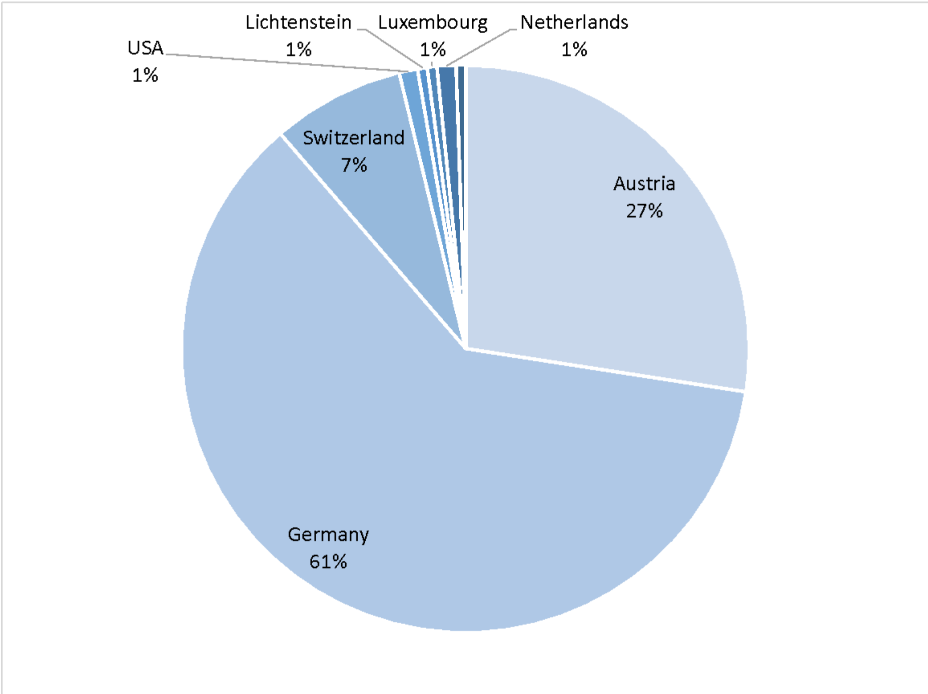


Figure 2. Distribution of respondents by country.

Most of the respondents represent the age group from 50 to 59 years old. The second biggest group of respondents as shown in Figure 3 was between 40 and 49 years old. Almost 90% of respondents were men. Trommer, Jarass and Kolarova (2015) find in their study that the mean age of early adopters of electric vehicles in Germany is 51 years, and the vast majority are men. These results are similar to the ones I find in my sample. Such distribution of age and gender among EV early adopters can be explained by affinity to the innovative technology and higher income of this group. Trommer, Jarass and Kolarova (2015) also found that EV users have significantly higher income compares to drivers of conventional cars and half of all private users of EVs have a university degree. Yet it is crucial to understand that today's electric vehicles' drivers are early adopters, but with further development of EVs the drivers mean characteristics may change and the described category will not be 100% representative of the majority of vehicle drivers in the future. However, for my current analysis it reflects the available on EV market situation very well and I can consider my sample as representative in this regard. This should be taken into account in the interpretation of the results of this study.

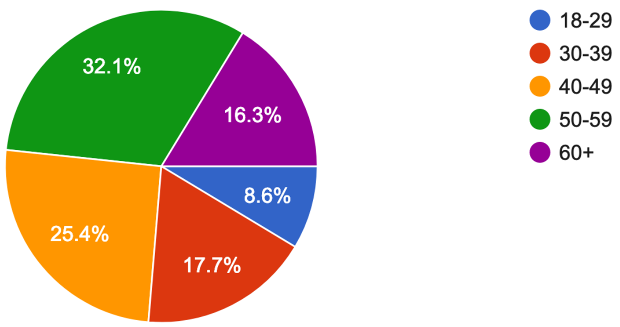


Figure 3. Distribution of respondents by age.

Respondents were also asked to specify their car brand and model. As it can be seen in Figure 4 the most common car in the survey was Tesla model S followed by Renault Zoe. The most common car in Germany is also Renault Zoe. Other popular in Germany electric cars like BMW i3, Nissan Leaf and Hyndai Ionic have also significant shares in my sample. In Figure 5 I compare the distribution of car models in my sample to the German market as a dominant share of respondents are from Germany. It can be seen that the distribution of car models in my research is comparable to the German market.

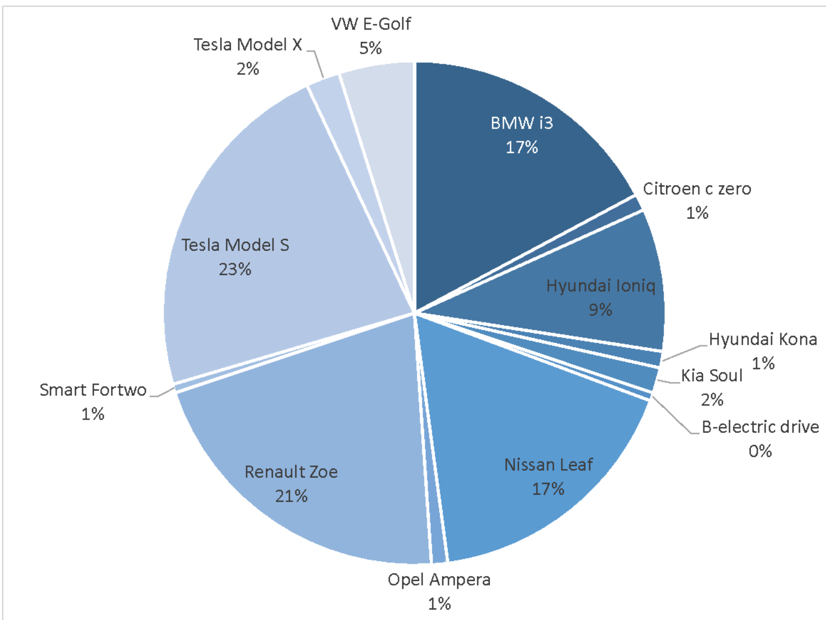


Figure 4. Distribution of cars.

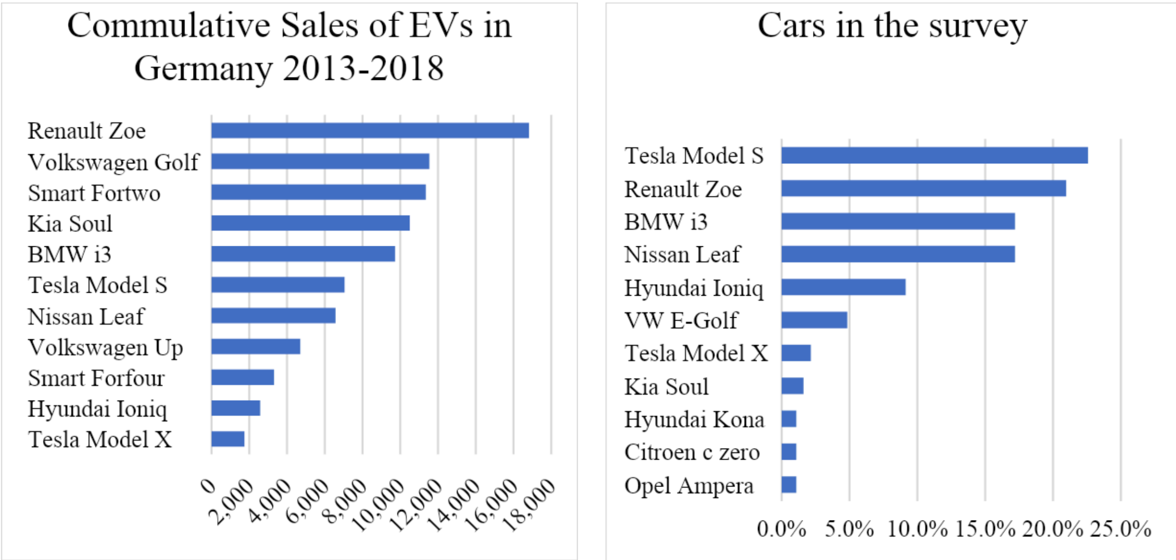


Figure 5. Comparison of cars.

4.2 Factors triggering the search for public charging possibility

I considered different triggers for charging event in the survey and in the app. One of the questions in the survey was “What triggers your decision to search a public charging station in most cases”. As it can be seen in Figure 6, the most common trigger is the range. This can be also seen in the data from the app in Figure 7: in 50% cases the charging event was recorded at a range below 50 km and in 82% cases below 100 km.

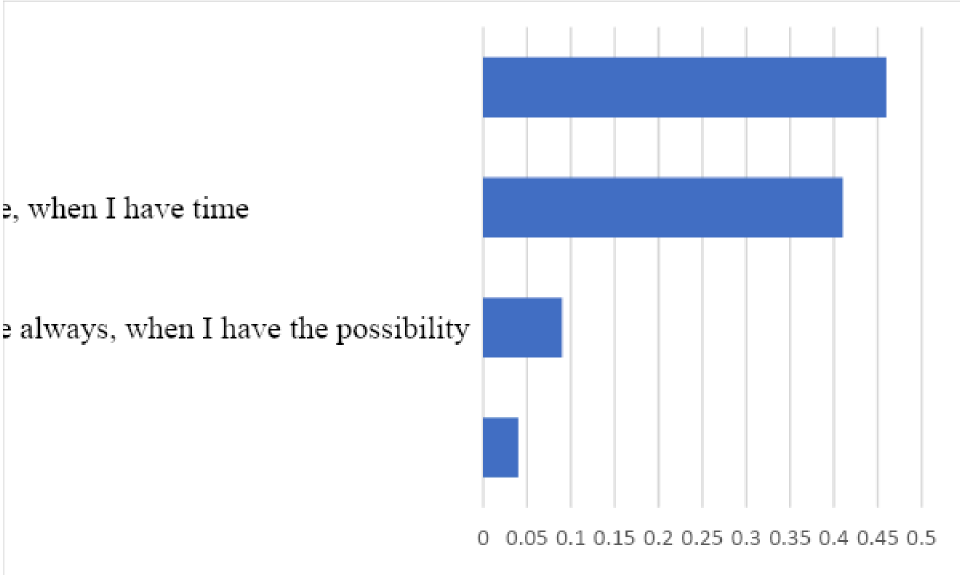


Figure 6. Triggers for searching of charging station.

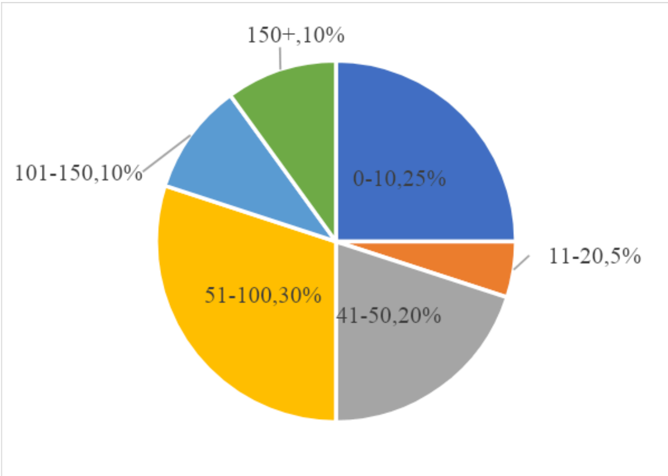


Figure 7. App data. Range as a trigger for searching of charging station.

4.3 Characteristics of the charging stations

The respondents were asked to mention the biggest problems of public charging infrastructure. The top 5 problems from the point of driver's view are presented in Figure 8. Due to the fact that the market is not consolidated yet there are many players who offer mobile applications and payment systems for public charging infrastructure. Not every card/payment system works at every charging station. This characteristic of today's public charging market is considered as a big pain for electric vehicle drivers.

Three out of five top problems of today's charging infrastructure are related to missing or not properly working information about the charging station. This problem could be explained by poor motivation and high outlay for charging station operators to maintain the information about their charging station on several different platforms and IT systems. Especially dynamic information about status and availability of charging stations demands high resources for a proper maintenance. These facts should be considered in design of new business models. Future business models should provide big enough gain to charging station operators in order to motivate them to maintain the information.

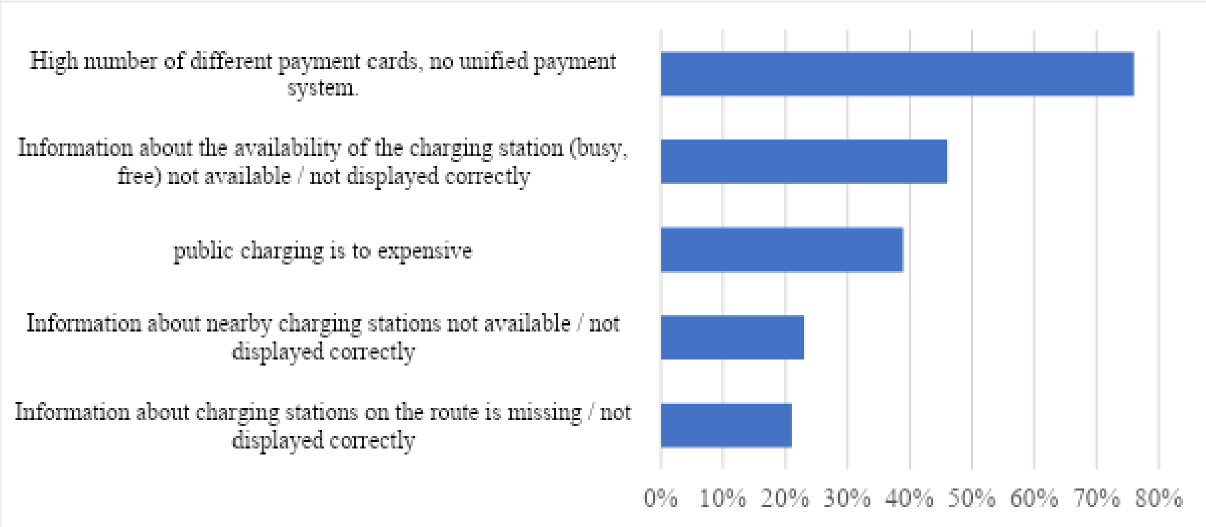


Figure 8. Top 5 problems of public charging infrastructure.

The respondents were also asked to rate the importance of the charging stations attributes. As it can be seen from Figure 9 the most important characteristic of a charging station according to the results of the survey is its power level. I assume this characteristic is considered by the electric vehicle drivers as the most important one due to the fact that it determines the time needed for charging. The second characteristic, which is considered to be important by electric vehicle drivers is the price for energy, followed by the distance to the charging station.

Surprisingly POI turned out to be not so important for respondents as the mentioned-above factors. But still the importance of POI lies above of the average. I assume, that the POI gets more important when choosing where to charge if other characteristics of charging stations are comparable. So information about POI could play a significant role in users' decision process.

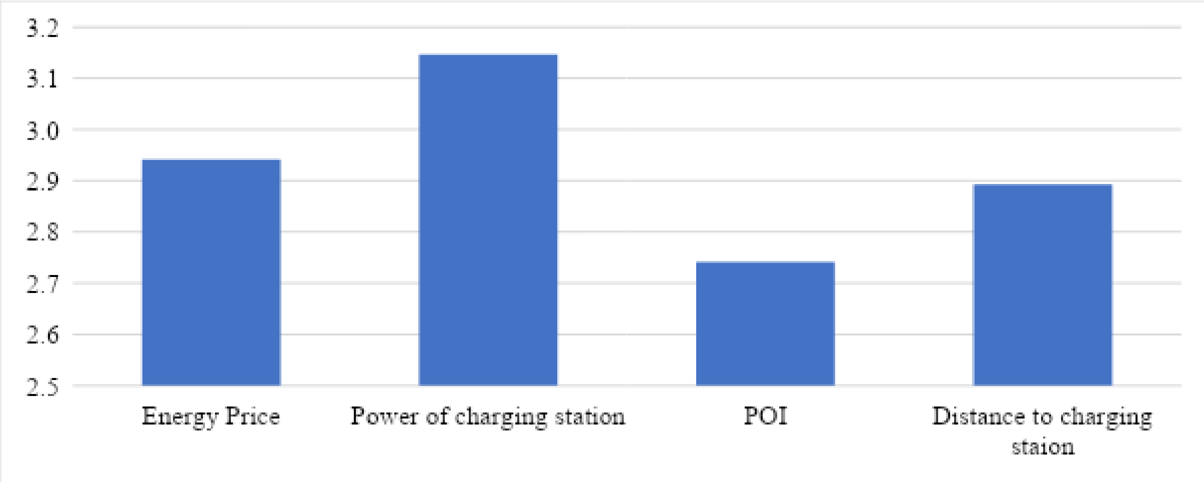


Figure 9. Importance of the charging stations attributes.

It is also worth mentioning that there is a weak positive correlation of 0.06 between the variables "importance of POI" and the answer "I charge always when I have the possibility". The correlation of these two parameters can be considered as an important factor in the context of further development of the charging infrastructure and also potential business models, as the drivers who prefer to charge more frequently also attached higher importance to the availability of the POI at the charging station.

4.4 *Incentives to make a detour*

As described above the factors which are suggested to have an impact on driver's decision to take a detour to charge his or her vehicle are discount on energy, discount on goods and the level of power. In the first two sections the respondents were asked whether they will make a detour for a discount on price of electricity, price of good available at the charging station or if they were offered a free coffee. The results of questions regarding discount on energy and goods are comparable to each other as the time of detour and the amount of financial gain for the driver in absolute terms were the same for these two factors. Therefore, in addition an analysis of the rationality of the decision making of electric vehicle drivers can be done. First results of these questions are presented in the Figures 8 and 9.

Average price for coffee in Germany in a cafe is 3,2€ (Merkur, 2016). 37% of respondents agreed to make the 10 minutes detour for a free cup of coffee. This corresponds with the financial gain of 3,3€ for the same detour resulting from both other groups of questions. The deviation between the price for coffee in a cafe and the price for coffee is calculated with help of the interpolation of the results of questions regarding discounts for energy and goods is very small. This decision is highly rational.

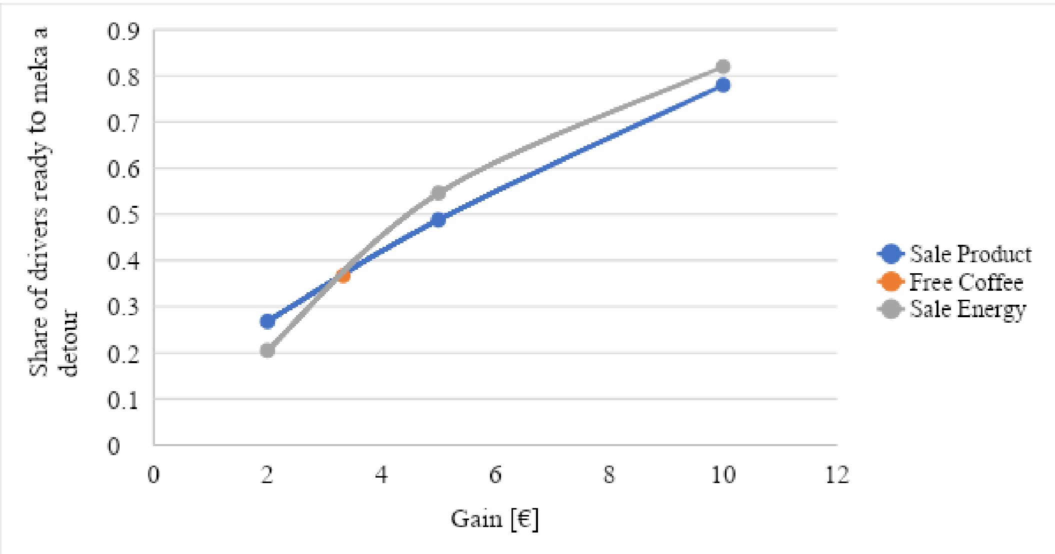


Figure 10. Descriptive results of the choice experiment.

5. Main results

5.1 Regression analysis of the choice experiment.

The main goal of my research is to evaluate the impact of such parameters as price (discounts) and time on preferences of users to charge their electric vehicles on public charging stations.

The main models that I used to analyze the results of the discrete choice experiment are conditional logit and alternative specific logit. The first model does not allow to include respondents' specific characteristics, while the second one does. My dependent variable in both models is the decision to make a detour, which is equal to 1 if the respondents agreed to detour and 0 otherwise. The results of the regressions are presented below.

In the first model the impact of discount on energy and time of detour on the decision of the electric vehicle drivers are analyzed. The variable "price" describes the size of discount on energy.

EV driver's decisions to make a detour		
price	0.302***	(0,026)
time	-0.158***	(0,021)
N	1116	

Robust standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01
The dependent variable is a binary, reflecting EV driver's decision to make a detour.

Table 3. Results of discrete choice experiment with discount on energy.

According to the results both factors have a significant impact on the choice of the electric vehicle drivers. The odds ratios are shown in Table 3. The odds rations should be interpreted as the change in the odds of the outcome for a one-unit increase in the predictor. An odds ratio greater than one means that the predictor increases the odds, less than one it decreases the odds and, if it is one, or not significantly different to one, it has no effect.

According to the results increasing the discount on energy at the charging station by 1 euro increases the odds of making a detour for charging by 30%, at the same time a 1-minute increase in time of the detour decreases the odds of making a detour by 16%.

Similar but smaller effect is found for discounts on goods. The result for discount on offer is presented in Table 4. Analyzing the choice set with level of power I also find both factors have a significant impact on decision to make a detour. The result for power is presented in Table 5. Increasing the power level by 1 kilowatt increases chances that EV driver will make a detour by roughly 7%. Looking at these 3 tables, it can be seen that in terms of size of the effect discount on energy has the highest impact on decision to make a detour.

EV driver's decisions to make a detour		
discount_goods	0.0466***	(0,005)
Time	-0.127***	(0,023)
N	1116	

Robust standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01
The dependent variable is a binary, reflecting EV drivers decision to make a detour.

Table 4. Results of discrete choice experiment with discount on offer at charging station.

EV driver's decisions to make a detour		
power	0.0687***	(0,009)
time	-0.0951***	(0,024)
N	744	

Robust standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01
The dependent variable is a binary, reflecting EV drivers decision to make a detour.

Table 5. Results of discrete choice experiment with power of charging station.

As a second step of choice experiment analysis, I investigated the effect of gender, age and car price on the decision to charge the electric vehicle using alternative-specific conditional logit as a model. The results can be found bellow in Tables 6 to 8. In order to specify this model, I had to identify the base alternative which in my case was defined in the survey by the following parameters: no time delay, no detour and no discount on energy price or offer.

EV driver's decisions to make a detour		
price	0.370***	(0,030)
female	-0,69	(0,523)
age	-0.207*	(0,107)
log_price	-0.756***	(0,283)
_cons	6.717**	(2,995)
N	1116	

Robust standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01
The dependent variable is a binary, reflecting EV drivers decision to make a detour.

Table 6. Results of alternative-specific conditional logit with discount on energy.

As it can be seen from Table 6 discount on energy had a positive impact on the probability to make a detour to charge an EV. Further on, looking at the respondent-specific factors, gender has no statically significant effect on the charging decision, but the price of the car owned by the respondent showed an effect on the decision to make a detour (natural logarithm of the car price is used here and in all the further specification of the tested models). Age shows a negative impact on the decisions to a make a detour to charge an EV. Meaning holding other factors fixed elder people are less likely to choose alternative charging station and make a detour. Same effect is observed for the price of the car owned by the respondent meaning holding other factors fixed drivers with more expensive cars have lower probability to make a detour and prefer to stick to the base alternative with no monetary gain and no loss in term of additional time.

EV driver's decisions to make a detour		
discount_goods	0.0564***	(0,005)
female	0,498	(0,526)
age	-0,167	(0,105)
log_price	-0,35	(0,254)
_cons	2,642	(2,728)
N	1116	

Robust standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01
The dependent variable is a binary, reflecting EV drivers decision to make a detour.

Table 7. Results of alternative-specific conditional logit with discount on offer at charging station.

Similar model was tested with discount on offered goods or services at a charging station. As it can be seen from the Table 7 in this specification the size of the discount is again statistically significant and positive, meaning higher discounts increase the probability of detour, however neither gender nor price of the car or age are statistically significant. Age is close to be weakly statistically significant, but still not. Such results may suggest that discount on energy and goods is perceived in a different way by electric vehicle drivers and have a different utility even if the absolute size of the personal monetary profit is the same. While talking about energy discount we observe difference in socio-demographic characteristics, and they are not significant anymore when discount on goods is added in the model.

Further analysis – power of charging station supports the results of conditional logit for this choice set, with increasing power level the probability to make a detour also increases, however none of the included respondent specific characteristics is statistically significant in this specification. Results for conditional logit with power of charging station are presented in table 8.

EV driver's decisions to make a detour		
power	0.0515***	(0,006)
female	0,359	(0,592)
Age	-0,0452	(0,109)
log_price	-0,36	(0,269)
_cons	3,098	(2,888)
N	744	

Robust standard errors in parentheses

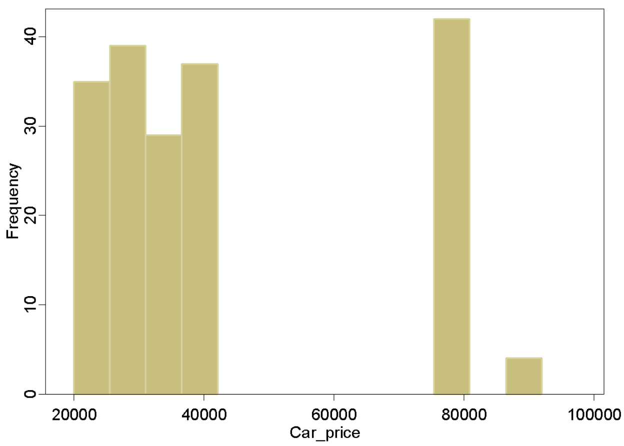
* p<0.1, ** p<0.05, *** p<0.01

The dependent variable is a binary, reflecting EV driver’s decision to make a detour.

Table 8. Results of alternative-specific conditional logit with power of charging station.

5.2 Dependency between car price and the decision to make a detour.

As the price of the car was one of the factors that showed interesting effect in the tested model, I have decided to investigate in detail the relation between this factor and the decision to make a detour.



Car_price	Freq.	Percent	Cum.
20000	2	1.08	1.08
22000	1	0.54	1.61
23000	32	17.20	18.82
30000	39	20.97	39.78
31400	3	1.61	41.40
33300	17	9.14	50.54
36000	9	4.84	55.38
37000	2	1.08	56.45
37550	32	17.20	73.66
39200	1	0.54	74.19
40000	2	1.08	75.27
80000	42	22.58	97.85
92000	4	2.15	100.00
Total	186	100.00	

Figure 11. Distribution of the car price.

Figure 11 shows the distribution of the car price in my sample, which as it can be seen from the data, is not normal. However, such distribution of the price is more or less representative for the current electric vehicle market. There are not so many cars on the market with the price between 40 and 80 thousand, while a wide variety of EVs are sold for the price of around 30 to 40 thousand euros and significant share is sold for more than 80 thousand. This can be explained by high popularity of premium car brand Tesla.

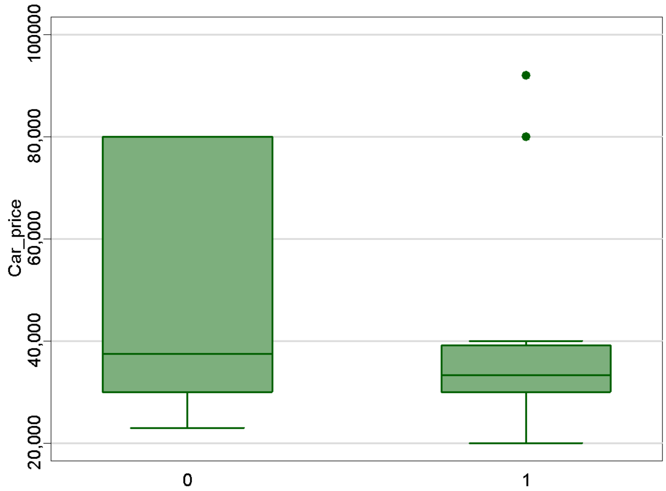


Figure 12. EV price distribution in the investigated sample.

Figure 12 shows the decision to make a detour in exchange for 10€ discount on energy by car price (1=agreed, 0=did not agree).

5.3 Testing differences in means by car price

In this section I use statistical test in order to measure the difference in means of above-mentioned variables by car price. In this way I want to check whether the variables discount on energy and discount on price are statistically comparable.

Group comparison: EV drivers’ decision to make a detour with 10% discount on goods by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	49	38335,71	2471,715	17302	33366	43305,43
No Detour	137	45231,02	2011,319	23541,88	41253,52	49208,53
Combined	186	43414,52	1630,314	22234,52	40198,12	46630,91
Difference		-6895,308	3676,123		-14148,08	357,464
Difference:	*-6895,308*	*t statistics:*	*(-1.88)*			

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 13. Results of ttest applied to the 10% discount on offer at charging station.

Group comparison: EV drivers’ decision to make a detour with 2€ discount on energy by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	35	37285,71	3127,717	18503,83	30929,43	43642
No Detour	151	44835,1	1858,082	22832,5	41163,7	48506,49
Combined	186	43414,52	1630,314	22234,52	40198,12	46630,91
Difference		-7549,385	4145,333		-15727,88	629,1095
Difference:	*-7549,385*	*t statistics:*	*(-1.82)*			

t statistics in parentheses

* p<0.05,** p<0.01, *** p<0.001

Table 14. Results of ttest applied to the 2€ discount on energy.

As it can be seen from Tables 13 and 14 there is no statistically significant difference in mean price of the car between the groups who agreed or did not agreed to make a detour for discount of 10% on goods and same is observed for discount of 2 euros on energy.

Group comparison: EV drivers' decision to make a detour with 25% discount on goods by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	89	41035,96	2199,893	20753,75	36664,13	45407,78
No Detour	97	45596,91	2376,468	23405,49	40879,66	50314,16
Combined	186	43414,52	1630,314	22234,52	40198,12	46630,91
Difference		-4560,952	3255,186		-10983,24	1861,335
Difference:	*-4560,952*	*t statistics:*	*(-1.40)*			

t statistics in parentheses

* p<0.05, ** p<0.01,***
p<0.001

Table 15. Results of ttest applied to the 25% discount on offer at charging station

Group comparison: EV drivers' decision to make a detour with 5€ discount on energy by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	99	39976,26	2041,857	20316,22	35924,26	44028,26
No Detour	87	47327,01	2546,222	23749,58	42265,29	52388,73
Combined	186	43414,52	1630,314	22234,52	40198,12	46630,91
Difference		-7350,749	3231,176		-13725,67	-975,8313
Difference:	*-7350,749*	*t statistics:*	*(-2.27)**			

t statistics in parentheses

* p<0.05,** p<0.01, ***
p<0.001

Table 16. Results of ttest applied to the 5€ discount on energy.

Group comparison: EV drivers' decision to make a detour with 50% discount on goods by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	143	43473,08	1879,958	22481,03	39756,75	47189,4
No Detour	43	43219,77	3301,959	21652,39	36556,14	49883,39
Combined	186	43414,52	1630,314	22234,52	40198,12	46630,91
Difference		253,3095	3877,519		-7396,804	7903,423
Difference:	*253,3095*	*t statistics:*	*(-0.07)*			

t statistics in parentheses

* p<0.05,** p<0.01, ***
p<0.001

Table 17. Results of ttest applied to the 50% discount on offer at charging station.

Group comparison: EV drivers' decision to make a detour with 10€ discount on energy by car price

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Detour	151	42515,23	1795,37	22061,85	38967,76	46062,71
No Detour	35	47294,29	3867,71	22881,70	39434,15	55154,43
Combined	186	43414,52	1630,31	22234,52	40198,12	46630,91
Difference		-4779,05	4167,66		-13001,60	3443,49
Difference:	*-4779,05*	*t statistics:*	*(-1.15)*			

t statistics in parentheses

* p<0.05,** p<0.01,***
p<0.001

Table 18. Results of ttest applied to the 10€ discount on energy.

Results for greater amounts of discounts on energy price and offers near to charging station are presented in tables 15, 16, 17 and 18. The higher is the discount on energy or goods the lower is difference in the mean car price between the groups who agreed or did not agree to make the detour.

Based on the results of "ttest" mean comparisons of car price and decision to make a detour, we can see that the respondents perceived discount on goods and discount on energy in a different way: for instance, we observe no statistically significant difference in the mean of car price for discount on goods of 25% (which according to the way the question was formulated is equivalent to 5€), but there is a statistically significant difference in the mean price of the car for decision to make a detour for a discount on energy of 5 eur.

Although such results should be interpreted with cautious, we can explain the observed phenomenon by several things: first according to recent studies by R. Thaler (2015) people react differently to absolute and percentage values although the amount of profit for the respondent is the same, further on there might be a difference in perceived value of goods and energy in the context of making decision regarding the charging of the car. These results are confirmed in the alternative specific conditional logit model.

6. Implications for new business models in context of charging.

In this section I am going to suggest two possible business models for e-mobility service providers. E-mobility service providers are intermediaries between charging station operators and drivers of electric vehicles. They provide a smartphone app with a possibility to find a charging station and to pay for a charging event. The most common business model of e-mobility service providers is to sell the energy to the drivers with a certain margin. The margin of e-mobility service providers varies a lot and dependents on the strategic goals of the company. Some of them are independent companies. There are also many e-mobility service providers owned by grid operators. In such scheme business processes can be optimized in the whole organization. For example, in order to get enough EV-users to be able to increase the revenue from energy sales a higher margin of e-mobility service providers could be sacrificed in order to reduce the price for energy. Another way to optimize the cost structure of the whole organization is to reduce the grid costs by incentivizing users to stabilize the grid by charging at suitable charging stations. In that case the cost for the maintenance of the grid can be reduced and the profit of the whole organization increases.

The ideas for both business models are derived from findings in this master thesis. The technical preconditions for both business models are high level of connectivity of stakeholders: vehicles, charging station operators, e-mobility service providers. Charging stations should be able to send real-time data about availability and charging event. As mentioned in chapter 4.3 it is crucial to create big enough gain through business model for charging station operators in order to motivate them to invest in modern connectivity hardware and to maintain the information.

Looking into results of my survey regarding driver's mobile application preferences we see that only 28% of respondents were fully satisfied with the app for search of charging stations that they are currently using. More than 76% of respondents indicated the search function as important. 22% of respondents would appreciate if the app will show them additional offers at charging stations, for example discounts on offers at points of interests near charging stations. More than 50% of respondents would even prefer to get personalized suggestions of charging stations and points of interests at the right moment from the app. More than 74% of respondents would share their vehicle data in order to improve the functions of the mobile application. As described in chapter 4.1 electric vehicle owners have significantly higher incomes than drivers of conventional cars, which makes them an interesting target audience and creates a supplementary incentive for charging stations and points of interest to create and maintain targeted offers for these drivers.

One of the key findings in my research is the willingness of users to make a detour in exchange for different incentives. Although the effect of sale for a product or service offered near to charging station is weaker than the effect of discount on energy it still motivates drivers to choose another charging station and make a detour. Both variables are significant. In both cases discount on energy and discount on offers near charging stations owners of less expensive cars are more likely to take the detour. However, in the case of discount on energy even owners of relatively expensive cars are ready to take the detour.

Summarized: drivers of electric vehicles are not happy with currently available mobile applications, they are ready to take a detour in exchange for some economic gain and they demonstrated an interest in the app that will suggest them charging stations and provide them information on special offers near the charging station. In addition, their income is significantly higher than of drivers of conventional cars, what makes them attractive customers from the prospective of the managers of points of interest.

6.1 Dynamic price management

This section was removed due to ongoing related commercial and research activities. Please reach out to me if you are interested in obtaining this information.

6.2 Loyalty program for charging stations and POIs

This section was removed due to ongoing related commercial and research activities. Please reach out to me if you are interested in obtaining this information.

7. Conclusions

In this master thesis I investigated EV drivers' decision to make a detour to charge their vehicles at the public charging station as well as the incentives which can increase the probability of the detour. The tested incentives include discount on the price of kWh, discount on offered at the charging station goods, and different level of power at the charging station. In order to answer my research question, I conducted a survey with 186 EV drivers. My sample is comparable with the majority of today's electric vehicle users. Using this sample quantitative analysis can be done and implications for business models can be suggested.

My analysis shows, that both discount on energy and discount on offers near charging station have a positive impact on the decision to make a detour. That means, that with help of these incentives the behavior of electric vehicle drivers can be changed and the distribution of electric vehicles between charging stations can be affected. This result can help to solve the problems of stakeholders in electric mobility eco-system. Better distribution will increase the utilization of charging stations and may reduce peak loads in the grid. Although I conducted a survey with stated preferences and not an actual experiment where drivers could behave differently compared to what they claim in a survey setting, the results of my research can be used as a first input in potential business models.

Suggested in this master thesis business models focus on increasing of the utilization of charging stations and on points of interest near charging stations. The idea behind the new business models for electric mobility providers is to create value for charging station operators, drivers, and point of interests.

8. Limitations and further research

In my master thesis I considered mainly German and Austrian markets. The next step in this topic could be the test of the hypothesis with other markets. Especially USA and China are relevant, as the share of electric vehicles is growing very fast there.

Another aspect, that was not considered in this work is the impact of other factors on the decision. I assume that the decision to make a detour is highly depended on user's current situation and trip purpose. If the person is in a hurry the monetary incentive to make a detour will not have the same effect as when the driver has enough time as the value of time will be higher in this situation.

Further on, as any other survey my research also suffers from the so-called survey bias, meaning that the respondents self-reported choice may differ to the actual decision to make a detour in real life. So further research using real observational data is required to have a better understanding of EV driver's decision to make a detour. This can be achieved by doing experiments with help of mobile applications.

9. Appendix

2. **1.1 Welches Elektroauto fahren Sie (Marke, Modell)?** *

Mark only one oval.

- BMW i3
- Renault Zoe
- VW E-Golf
- Smart Fortwo
- Kia Soul
- Tesla Model S
- Tesla Model X
- VW Up
- Hyundai Ioniq
- Nissan Leaf
- Other: ______________

3. **1.2 Aus welchem Land kommen Sie?** *

Mark only one oval.

- Deutschland
- Österreich
- Schweiz
- USA
- Other: ______________

4. **Geben Sie bitte Ihr Geschlecht an** *

Mark only one oval.

- Mann
- Frau
- Möchte ich nicht angeben

5. **Geben Sie bitte Ihr Alter an** *

Mark only one oval.

- 18-29
- 30-39
- 40-49
- 50-59
- 60+

6. **Was sehen Sie als Hauptproblem beim öffentlichen Laden Ihres Elektrofahrzeuges? (mehrere Antwortmöglichkeiten sind möglich):** *
Check all that apply.

- [ ] Information über Ladestationen in der Nähe nicht vorhanden/nicht richtig angezeigt
- [ ] Information über Ladestationen auf der Route nicht vorhanden/nicht richtig angezeigt
- [ ] Information über Verfügbarkeit der Ladestation (besetzt, frei) nicht vorhanden/nicht richtig angezeigt
- [ ] Man kann die Ladestation nicht reservieren
- [ ] Hohe Anzahl unterschiedlichen Ladekarten/Bezahlsysteme
- [ ] Öffentliches Laden zu teuer
- [ ] Ich habe keine Probleme.
- [ ] Betrifft mich nicht. Ich lade nicht öffentlich.
- [ ] Other: ______________________

7. **Wie oft laden Sie Ihr Elektrofahrzeug halböffentlich (z.B. Parkplatz eines Kaufhauses oder Supermarktes)?** *
Mark only one oval.

- ( ) Täglich
- ( ) 2-3 Mal pro Woche
- ( ) 1 Mal pro Woche
- ( ) 2-3 Mal pro Monat
- ( ) 1 Mal pro Monat oder weniger
- ( ) Nie

8. **Wie oft laden Sie Ihr Elektrofahrzeug öffentlich?** *
Mark only one oval.

- ( ) Täglich
- ( ) 2-3 Mal pro Woche
- ( ) 1 Mal pro Woche
- ( ) 2-3 Mal pro Monat
- ( ) 1 Mal pro Monat oder weniger
- ( ) Nie

9. **Wie oft laden Sie Ihr Elektrofahrzeug zuhause oder beim Arbeitgeber?** *
Mark only one oval.

- ( ) Täglich
- ( ) 2-3 Mal pro Woche
- ( ) 1 Mal pro Woche
- ( ) 2-3 Mal pro Monat
- ( ) 1 Mal pro Monat oder weniger
- ( ) Nie

10. **Bewerten Sie bitte auf der Skala 1 bis 4 welche Eigenschaften der Ladestation Ihnen am wichtigsten sind? (4 die wichtigste, 1 am wenigsten wichtig)** *

Mark only one oval per row.

	1	2	3	4
Strompreis				
Ladeleistung				
POI (Point of interest z.B. Supermarkt, Restaurant neben der Ladestation)				
Entfernung zu der Ladestation				

Ortsbezogene Angebote

11. **Würden Sie einen Umweg in Kauf nehmen, um ein personalisiertes, ortsbezogenes Angebot wahrzunehmen, wie z.B. ein Rabatt auf einen Einkauf oder eine Dienstleistung während des Ladens?** *

Mark only one oval.

Ja

Nein

12. **Stellen Sie sich vor Sie müssen laden und suchen nach einer Ladestation. Würden Sie 10 Min Umweg in Kauf nehmen, um 10% Rabatt auf einen Einkauf im Wert von 20€ während des Ladens zu bekommen?** *

Mark only one oval.

Ja

Nein

13. **Würden Sie 10 Min Umweg in Kauf nehmen, um 25% Rabatt auf einen Einkauf im Wert von 20€ während des Ladens zu bekommen?** *

Mark only one oval.

Ja

Nein

14. **Würden Sie 10 Min Umweg in Kauf nehmen, um 50% Rabatt auf einen Einkauf im Wert von 20€ während des Ladens zu bekommen?** *

Mark only one oval.

Ja

Nein

15. **Stellen Sie sich vor Sie müssen laden und suchen nach einer Ladestation. Würden Sie 10 Min Umweg in Kauf nehmen, um kostenlosen Kaffee während des Ladevorgangs zu genießen?** *

Mark only one oval.

Ja

Nein

16. **Wenn Sie unterwegs sind, bewerten Sie wie wichtig es Ihnen bei der Wahl der Ladestation ist, ob Sie ein "Point of Interest" (z.B. eine Einkaufsmöglichkeit, Arbeitsplatz mit WiFi,...) neben der Ladestation vorfinden? (1 = nicht wichtig; 4 = sehr wichtig)** *
Mark only one oval per row.

	1	2	3	4
In der Stadt	◯	◯	◯	◯
Überland / auf der Autobahn	◯	◯	◯	◯

17. **Welche ortsbezogenen Angebote würden Sie interessieren?** *

____

18. **Welche Kategorie der POIs wären für Sie an der Ladestation am interessantesten?** *
Mark only one oval.

- ◯ Lebensmittelmarkt
- ◯ Tankstellenshop
- ◯ Arbeitsplatz mit WiFi
- ◯ Restaurant
- ◯ Kaffee
- ◯ Frisur oder ähnliche Dienstleistung
- ◯ Shop mit Artikel für Ihr Auto
- ◯ Einkaufszentrum
- ◯ Other: ______________________________

Stromnachlass

19. **Würden Sie einen Umweg in Kauf nehmen, um einen Nachlass für den Strom an der Ladestation zu bekommen?** *
Mark only one oval.

- ◯ Ja
- ◯ Nein

20. **Stellen Sie sich vor Sie müssen laden und suchen nach einer Ladestation. Sie haben die Option für eine weiter entfernte Ladestation einen Nachlass im Wert von 2€ auf das Laden zu erhalten. Würden Sie dafür 10 Min Umweg in Kauf nehmen?** *
Mark only one oval.

- ◯ Ja
- ◯ Nein

21. **Würden Sie für den Nachlass im Wert von 5€, 10 Min Umweg in Kauf nehmen?** *
Mark only one oval.

- ◯ Ja
- ◯ Nein

22. **Würden Sie für den Nachlass im Wert von 10€, 10 Min Umweg in Kauf nehmen?** *
Mark only one oval.

- Ja
- Nein

23. **Würden Sie für kostenloses Laden 10 Min Umweg in Kauf nehmen?** *
Mark only one oval.

- Ja
- Nein

Ladeleistung

24. **Würden Sie einen Umweg in Kauf nehmen, um die Ladestation mit höherer Leistung zu erreichen?** *
Mark only one oval.

- Ja
- Nein

25. **Würden Sie einen Umweg von 10 Minuten in Kauf nehmen, um die Ladestation mit der 22 kW Leistung statt die Ladestation mit 11 kW Leistung zu erreichen?** *
Mark only one oval.

- Ja
- Nein

26. **Würden Sie einen Umweg von 10 Minuten in Kauf nehmen, um die Ladestation mit der 50 kW Leistung statt die Ladestation mit 11 kW Leistung zu erreichen?** *
Mark only one oval.

- Ja
- Nein

App

27. **Wodurch wird Ihre Entscheidung eine öffentliche Ladestation zu suchen in den meisten Fällen ausgelöst/getriggert?** *
Mark only one oval.

- Ladezustand der Batterie bzw. Restreichweite
- Sie suchen eine Ladestation dann, wann Sie gerade Zeit haben zum Laden
- Sie Laden einfach immer, wenn es die Möglichkeit gibt zu laden (z.B. während Sie einkaufen)
- Ich lade nicht öffentlich
- Sonstiges

28. **Benutzen Sie im Moment eine Elektromobilitäts-App? Wenn ja, welche?** *

29. **Wie zufrieden sind Sie mit den Apps zur Suche der Ladestationen?** *
Mark only one oval.

	1	2	3	4	
Unzufrieden	◯	◯	◯	◯	Sehr zufrieden

30. **Welche Attribute wären Ihnen am wichtigsten, in einer App die Ihnen den Ladevorgang vereinfachen soll (mehrere Antworten sind möglich)?** *
Check all that apply.

- [ ] Finden der Ladestationen
- [ ] Einheitliches Bezahlsystem
- [ ] Übersicht der persönlichen Ladedaten z.B. monatliche Ausgaben fürs Laden, gefahrene Kilometer
- [ ] Zusätzliche Angebote, z.B. Rabattaktionen bei den POIs neben der Ladestationen
- [ ] Neuigkeiten aus der Welt der Elektromobilität
- [ ] Übersichtliche Darstellung der Auto-Daten
- [ ] Reservierung von Ladestationen
- [ ] Prognose der Wahrscheinlichkeit ob eine Ladestation belegt wird zum Zeitpunkt wann Sie dort ankommen

31. **Würden Sie es begrüßen, dass Ihnen Ihre App automatisiert und rechtzeitig (z.B. wenn Ihre Restreichweite gering ist) eine Ladestation vorschlägt und dabei Ihre Präferenzen bezüglich POI (Point of Interest) und des Angebotes an der Ladestation berücksichtigt?** *
Mark only one oval.

- ◯ Ja, ich würde personenbezogene Vorschläge begrüßen.
- ◯ Einen Vorschlag ja. Aber nicht personenbezogen.
- ◯ Nein

32. **Würden Sie Ihre Fahrzeugdaten teilen, um die Funktionen der App zu verbessern und auf Ihre Bedürfnisse besser anzupassen (Dabei werden Ihre Daten selbstverständlich vertraulich behandelt)?** *
Mark only one oval.

- ◯ Ja
- ◯ Nein

33. **Welche andere Funktion der App würden Sie sich wünschen?** *

____

34. **Wie viel wären Sie bereit für eine App zu zahlen, die die Suche nach Ladestationen deutlich einfacher macht und den Prozess rund ums öffentliche Laden einfacher macht?** *
Mark only one oval.

- ◯ 1 € pro Monat
- ◯ 3 € pro Monat
- ◯ 5 € pro Monat
- ◯ 10 € pro Monat
- ◯ Ich würde nicht für eine App zahlen

35. **[Optional] Bitte geben Sie uns Ihre E-Mail Adresse, falls Sie informiert werden möchten, sobald die App mit der automatisierten Funktion zum Vorschlag der Ladestation fertig ist.**

36. **[Optional]. Bitte geben Sie Ihren Nickname/Username für die App ein, mit der Sie uns helfen Ihr Benutzerverhalten besser zu verstehen. Die App dient nur zum Sammeln der Daten und hat noch keine oben beschriebene Funktionen.**

37. **[Optional] Wie am Anfang angekündigt gibt es noch eine App die ausschließlich der Datensammlung für die Studie dient. Diese App hat noch keine o.g. Funktionen. Wenn Sie uns durch Teilen der Daten zu Ihren Ladevorgängen unterstützen möchten, geben Sie hier bitte Ihre E-Mail an, damit wir Ihnen die Details dazu schicken können. So können wir "theoretische" Erkenntnisse aus dem Fragebogen mit realen Daten ergänzen.**

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