Charles University
Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Willingness to pay for electricity-driven passenger vehicles

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Academic Year: **2016/2017**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, May 18, 2017

Signature

Acknowledgments

The author is very grateful to Mgr. Milan Ščasný, Ph.D. for his supervision, guidance and unceasing patience, to Mgr. Iva Zvěřinová and Mikołaj Czajkowski, Ph.D. for their helpful advice. The author would like to give special thanks to her friends and family, especially her mom. Without their unconditional support and tireless perseverance she would have given up pursuing this Master's Degree a long time ago.

The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 681228 (GEMCLIME). Data were gathered within a research project DEFINE ("Development of an Evaluation Framework for the Introduction of Electromobility" funded by the Polish NCBiR (Centre for Research and Development). Responsibility for any errors remains with the author.

Abstract

This thesis analyses stated preferences for 4 different types of passenger vehicles (conventional, hybrid electric, plug-in hybrid, and battery electric vehicles). The discrete choice experiment survey was conducted in Poland in 2014. With the use of latent class model it was possible to identify and describe distinct segments in the population with varying preferences for the propulsion technologies: groups with strong and weak preferences for conventional vehicles, segments preferring pure hybrid and plug-in hybrid electric vehicles, and a class in favour of battery electric vehicles. Even though it was found that on average consumers would require compensation up to 22,200zł (€5,311) to switch to using an electric vehicle, respective segments in the population would be willing to pay around 10,100zł (€2,417) for this change in case of pure hybrid, around 21,400zł (€5,128) in case of plug-in hybrid, and around 92,800zł (€22,199) in case of battery electric vehicles.

JEL Classification	D12, Q42, Q51, R40
Keywords	willingness to pay, discrete choice experiments, stated preferences, consumer preferences, alternative fuel vehicles, electromobility

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Abstrakt

Predložená práca analyzuje vyjadrené preferencie k 4 typom osobných vozidiel (k vozidlám konvenčným, čisto hybridným, hybridným s možnosťou napájania a elektrickým na batériu). Pre získanie dát bol použitý výberový experiment, vykonaný v Poľsku v roku 2014. Pomocou modelu latentných tried bolo možné identifikovať a popísať skupiny v populácii, ktoré sa medzi sebou líšia odlišným postojom k uvedeným technológiá: skupiny so silnou a slabou preferenciou ku konvenčným autám, segmenty preferujúce vozidlá hybridné a hybridné s možnosťou napájania, a skupinu uprednostňujú elektrické autá na batériu. Aj napriek tomu, že v priemere by spotrebitelia vyžadovali kompenzáciu do výšky až 22,200zł (€5,311), aby prešli od používania konvenčného vozidla k vozidlu na elektrinu, odpovedajúce skupiny v populácii by za túto zmenu boli ochotné zaplatiť okolo 10,100zł (€2,417) v pripáde čisto hybridného vozidla, približne 21,400zł (€5,128) v prípade hybridného vozidla s možnostťou napájania, a okolo 92,800zł (€22,199) v prípade elektrického vozidla na batériu.

Klasifikace JEL D12, Q42, Q51, R40
Klíčová slova ochota platiť; výberový experiment; vyjadrené preferencie; spotrebiteľské preferencie; vozidlá na alternatívny pohon; elektromobilita

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Acronyms

ASC alternative specific constant

AFV alternatively fuelled vehicle — CNG, LPG, BEV, HEV, PHEV, BEV, HV, biofuel

BEV battery electric vehicle

CNG compressed natural gas

CV conventional vehicle

EV electricity driven vehicle

GEV generalized extreme value

GHG greenhouse gas

GV gasoline vehicle

HEV hybrid electric vehicle

HOV high-occupancy vehicle

HV hydrogen (fuel cell electric) vehicle

ICV internal combustion engine vehicle

LPG liquid propane gas

PHEV plug-in hybrid electric vehicle

R&D research and development

RP revealed preference

SP stated preference

V2G vehicle-to-grid electric vehicle

WTP willingness to pay

ZEV zero emission vehicle

Master's Thesis Proposal

Author	Bc. Inés Horváthová
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Proposed topic	Willingness to pay for electricity-driven passenger vehicles

Motivation The European Union has committed to take actions in mitigating global warming and climate change. One area of interest concerns "greener" decarbonized transportation using alternative fuels. In the Directive 2014/94/EU on the deployment of alternative fuels infrastructure member countries are prompted to incorporate national goals and measures to support the market for alternative-fuel vehicles into their national frameworks. Special focus is given to electromobility and natural gas (compressed and liquefied), which are on the edge of their commercial usage. Electricity-driven vehicles have the potential to reduce direct greenhouse gas emissions, air and noise pollution, and dependence on fossil fuels. With energy generated from renewable sources, electric vehicles can substantially contribute to climate-friendly and sustainable transportation. Even though there are undeniable efforts on the part of policy-makers and consequently also vehicle manufacturers to lead personal transportation towards greener and more efficient alternatives to conventional vehicles, the reluctance of car buyers towards all kinds of alternative-fuel vehicles (and electric vehicles in particular) remains. For instance, German government set an ambitious goal of 1 million registered electric vehicles by the year 2020, while at the end of 2013 only about 12,000 battery electric vehicles were registered in Germany (Hackbarth, Madlener, 2016). In Poland the Ministry of Energy assumes 1 million electric vehicles on Polish roads by 2025 and the National Action Plan for Clean Mobility sets target of 250 thousands electric cars by 2030 for the Czech Republic (NAP CM, 2015), while in 2015 only 5,675 and 1,292 electric vehicles (including hybrids) were registered for these two countries, respectively (ACEA, 2015). There still persist psychological and technical barriers to higher market penetration, mainly short driving range, long recharging time, high purchase prices and overall uncertainty. For the preparation and introduction of adequate policy measures that would incentivize the usage of electricity-driven vehicles, proper identification of these barriers, as well as analysis of individual preferences and estimation of willingness to pay for specific attributes of these vehicles is crucial. Existing studies on this topic suggest high heterogeneity of preferences, which differ among countries, socioeconomic characteristics of individual respondents and characteristics of the vehicles. Most of the existing studies are based in Northern American or Western European countries. The research studying consumer preferences in Poland within the ERA-NET DEFINE framework (Ščasný et al., 2015) was the first to study this topic in Central and Eastern European conditions. Building upon this research, which points toward high preference heterogeneity of Polish consumers for electricity-driven vehicles and their attributes, this work aims to further the understanding of this heterogeneity by dividing the population into appropriate number of classes, and finding the main choice determinants and their associated willingness-to-pay estimates in each distinct group with the use of latent class model.

Hypotheses

Hypothesis #1: There are distinct segments of consumers in the population with varying preferences towards electric vehicles.

Hypothesis #2: Consumers' preferences are influenced by their attitudes toward new technologies and the environment, as well as by the attitudes of their closest family members and friends.

Hypothesis #3: Consumers owning two or more vehicles are more likely to adopt an electric vehicle.

Methodology As the current market share of alternative-fuel vehicles, and electric cars in particular, is negligible, standard demand estimation techniques are not appropriate. In this case of low market share and still evolving technologies, potential demand can be estimated using stated preference (SP) methods (Hanemann,1984). The SP methods, especially discrete choice experiments (DCE), serve as useful tool to elicit preferences for very specific attributes of alternative fuel vehicles and thus provide support for policy. DCE studies utilize a survey in order to examine the tradeoffs between different goods or policies. In a typical such survey, respondents are presented with alternatives of a good described by a set of atributes, and are asked to rank or rate these alternatives, or to choose their most preferred one (Hanley et al., 2001). The alternatives differ from one another in two or more values of these attributes - levels. Even hypothetical levels of attributes can be included, such as the driving range of the electric vehicle that is better than any available on the market nowadays, in order to examine consumer preferences for such technological improvement. The responses can be used to estimate the marginal rates of substitution between attributes. If one of the attributes is cost, it is possible to calculate the marginal price of each attribute. If the "do nothing" or status quo option is included in the choice set, the experiments can be used to estimate the full value (WTP) of each alternative. It is assumed that the choice between the alternatives is driven by the respondent's underlying utility. The respondent's indirect utility is broken down into two components. The first component is deterministic, and is a function of the attributes of alternatives, characteristics of the individuals, and a set of unknown parameters, while the second component is an error term. Utility in such a form describes a random-utility model (RUM). In many applications, it is further assumed that the deterministic component of utility, is a linear function of the attributes and of the respondent's residual income. If the error terms are independent and identically distributed and follow a standard type I extreme-value distribution, one can derive a closed-form expression for the probability that respondent i picks alternative k out of K alternatives. These probabilities contribute to the likelihood in a conditional logit model (CL) and the coefficients are estimated using the method of Maximum Likelihood (McFadden, 1974). The CL model can be easily amended to allow for heterogeneity among the respondents. Specifically, one can form interaction terms between individual characteristics, such as age, gender, place of living, etc., and all or some of the attributes, and enter these interactions in the indirect utility function (Alberini et al., 2007). Implicit in the conditional logit model is the assumption of Independence of Irrelevant Alternatives (IIA), which states that the ratio of the odds of choosing any two alternatives depends only on the attributes of the alternatives being compared, and is not affected by the attributes of other alternatives. Appropriate Hausman test will be carried out in order to test for violations of this assumption (Hausman, McFadden, 1984). Along with a standard CL model, we will also apply a latent class model (LCM), which takes the preference heterogeneity into account. LCM allows for a segmentation of the population into distinct consumer groups, a specification of the size of these consumer groups in the population, and their detailed description by socio-demographic characteristics and attitudes. In contrast to the standard CL, LCM partly overcomes the restrictive independence of irrelevant alternatives assumption and deals with correlations of repeated choices of a single respondent (Swait, 2007). Furthermore, LCMs also seem to possess an advantage over mixed logit models (Greene and Hensher, 2003; Hess et al., 2011). The main assumption of LCM is the existence of S segments, classes or groups in the population, where the individuals belonging to a specific group are characterized by homogeneous utility function, while the preferences can differ between classes. The true class membership stays unobservable (Boxall and Adamowicz, 2002; Bujosa et al., 2010 Hence, an LCM consists of two separate probabilistic models, which are to be estimated simultaneously: 1. a choice model which explains individuals' choice among the available alternatives in the different choice occasions, conditional on belonging to a specific class and 2. a class membership model which assigns the decision-makers to the S distinct classes, based on their socio-demographic and/or attitudinal characteristics. For this thesis the data from a carefully prepared and properly pre-tested questionare, which included eight choice sets for each respondent, will be analysed. The survey in the form of structured computer-assisted web interviews using an e-panel managed by Millward Brown was conducted in Poland in 2014. In total 2613 Polish adults were interviewed.

Expected Contribution The expected contribution of this thesis can be found in furthering the understanding of preference heterogeneity in the setting of Polish car market. Better understanding of taste differences of car buyers could be of help for policy makers as well as decision-makers in the automotive industry, especially when attempting to accelarate the adoption of alternative-fuel vehicles and electric vehicles in particular. This can be achieved by specifically customizing their products or incentive schemes subject to the differences in preferences between consumer segments.

Outline

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4. Survey and data: Presentation of the experimental design of the study and summary statistics of the gathered data.
5. Results: Estimation results and description of the main findings.
6. Conclusion: Summary of the main findings and their implications.

Core bibliography

Alberini, A., Longo, A., Veronesi, M. (2007). Basic statistical models for stated choice studies. In: Kanninen,B.J. (Ed.), Valuing Environmental Amenities Using Stated Choice Studies – A Common Sense Approach to Theory and Practice. Springer, Dordrecht, 203-227.

Boxall, P. C., Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: a latent class approach. Environmental and resource economics, 23(4), 421-446.

Bujosa, A., Riera, A., Hicks, R. L. (2010). Combining discrete and continuous representations of preference heterogeneity: a latent class approach. Environmental and Resource Economics, 47(4), 477-493.

Carson, R.T., Louviere, J.J. (2011). A Common Nomenclature for Stated Preference Elicitation Approaches. Environmental and Resource Economics, 49(4), 539-559.

Directive 2014/94/EU of the European Parliament and of the Council on the deployment of alternative fuels infrastructure. (2014). O. J. L 307/1.

European Automobile Manufacturers Association.(n.d.). New Passenger Car Registrations by Alternative Fuel Type in The European Union.Retrieved from http://www.acea.be/uploads/press_releases_files/AFV_registrations_Q4_2015_FINAL.PDF

Greene, W. H., Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B: Methodological, 37(8), 681-698.

Hackbarth, A., Madlener, R. (2016). Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. Transportation Research Part A: Policy and Practice, 85, 89-111.

Hanemann, W. M. (1984). Welfare evaluations in contingent valuation experiments with discrete responses. American Journal of Agricultural Economics, 66(3), 332-341.

Hanley, N., Mourato, S., Wright, R. E. (2001). Choice Modelling Approaches: A Superior Alternative for Environmental Valuation? Journal of Economic Surveys, 15(3), 435–462.

Hausman, J., McFadden, D. L. (1984). Specification tests for the multinomial logit model. Econometrica: Journal of the Econometric Society, 1219-1240.

Hess, S., Ben-Akiva, M., Gopinath, D., Walker, J. (2011). Advantages of Latent Class Over Continuous Mixture of Logit Models. ITS Working paper, Institute for Transport Studies, University of Leeds, Leeds.

McFadden, D. L. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), Frontiers in Econometrics, New York: Academic Press.

Ministerstvo průmyslu a obchodu ČR. (2015). Národní akční plán čisté mobility. Praha: MPO.

Swait, J. (2007). Advanced choice models. In: Kanninen,B.J. (Ed.), Valuing Environmental Amenities Using Stated Choice Studies – A Common Sense Approach to Theory and Practice. Springer, Dordrecht, 229-293.

Ščasný, M., Zvěřinová, I, Czajkowski, M. (2015). Individual preference for the alternative fuel vehicles and their attributes in Poland. Submitted to EcoMod2015, Boston College, July 15-17, 2015.

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Chapter 1

Introduction

Transportation sector significantly contributes to air pollution, increasing levels of nitrous oxides and particulates, noise pollution, and global warming through emission of carbon dioxide. Within the sector, road transport is the largest contributor. Many governmental regulations worldwide have therefore been introduced in order to set environmental standards for individual vehicle's emissions and/or to stimulate the production and adoption of alternative fuel vehicles (AFVs). AFVs have the potential to tackle these problems, as well as to reduce dependency on fossil fuels.

Among AFVs belong vehicles that are not fuelled with conventional fuels (gasoline or diesel), but run on their alterantives, e.g. natural gas (liquefied petroleum gas, LPG, or compressed natural gas, CNG), biofuels (bioethanol or biodiesel, hydrogen, or electricity. There are several types of vehicles driven by electricity (EVs), varying in the source and the extent to which electric power is being utilized. Hybrid electric vehicles (HEVs), for example, can recuperate energy to achieve better fuel economy or better performance, but are otherwise run by an internal combustion engine (ICE). Plug-in hybrid electric cars (PHEVs), although still equipped with an ICE, allow to be powered entirely by electricity and also have a possibility of direct plug-in recharging. Fully battery electric vehicles (BEVs) are then solely run by electricity and hence require to be plugged-in to recharge, while fuel cell electric vehicles (HVs) use reaction of hydrogen with oxygen to run their electric motors.

In the Directive 2014/94/EU on the deployment of alternative fuels infrastructure the European Union has prompted member countries to incorporate national goals and measures to support the market for alternative fuel vehicles. Special focus is given to electromobility and natural gas, which are on the edge of their commercial usage. However, despite undeniable efforts on the part of policy-makers to lead personal transportation towards greener alternatives to conventional vehicles, the reluctance of car buyers towards all kinds of AFVs, and electric vehicles in particular, remains.

Electric vehicles are generally associated with high purchase prices, long recharging times, short driving ranges, insufficient charging stations infrastructure, and inadequate possibilities for servicing, which consequently result in overall uncertainty connected with this type of vehicles. Proper identification of these psychological and technical barriers to higher market penetration of EVs, estimating overall willingness to pay for improvements in these features, as well as estimating WTPs for these new technologies themselves, seem crucial in creating more effective and efficient government policies.

Previous research on this topic points towards high heterogeneity of preferences towards electricity-driven cars. Even though on average negative perception of this type of vehicles prevails in the population, results of Ščasný *et al.* (2015) suggest that there should be percentage of people who would actually be willing to pay to switch from using conventional vehicles to using their electrified alternatives.

The objective of this thesis is then to add to the understanding of this preference heterogeneity found by applying *latent class modelling* on the data. Utilizing this latent class framework it is possible to examine whether distinct segments with varying preferences for different electricity-driven vehicles actually exist in the population, what is the percentage representation of each class, and how these classes differ from each other in terms of observed characteristics, i.e. this thesis should add to the understanding of the observed preference heterogeneity.

The thesis is structured as follows: Chapter 2 introduces electric vehicles in general and presents the results of previous studies dealing with preferences for EVs and their characteristics. Chapter 3 explains the theory and methodology behind the results of this thesis. Chapter 4 describes in detail the experiment used when gathering the data, as well as the data itself. Chapter 5 presents the results from number of models, while Chapter 6 summarized the main findings.

Chapter 2

General characteristics and literature review

Even though many governments worldwide have implemented strong policies to stimulate production and adoption of electric vehicles (EVs), their current market penetration remains relatively low. It is believed that better knowledge of consumer preferences for this emerging technology can make the incentives more effective. For that reason many empirical studies regarding consumer preferences for EVs have been issued over the past decades. In order to gather relevant studies for this literature review the following databases were searched: EBSCO, ProQuest Central, Scopus, Web of Science and Google Scholar [1]. The keywords used for searching consisted of combination of either *willingness to pay, stated preferences, demand,* or *purchase* with either *electric, low carbon, hybrid, hydrogen, CNG, alternatively fueled,* or *clean-fuel* and with either *vehicle* or *car*. Many of the articles found included a short literature review, which enabled backward searching.

Only studies relying on economic approaches, on discrete choice analysis, were selected. Their overview can be found in Table 2.1. Since EVs penetration in the market is still relatively low, all the reviewed studies are based on stated preference (SP) data, although some combine both stated and revealed preference data (Brownstone *et al.* 2000; Axsen *et al.* 2009; Bočkarjova *et al.* 2013). SP data are collected using choice experiments in which respondents make choices from a given list of alternatives. These are described by varying levels of attributes, which can also be hypothetical. Using appropriate

[1] Last date of literature search was December 1, 2016

modelling techniques the taste parameters for individual attributes are then estimated, representing weights in the consumers' decision.

The attributes included in the reviewed studies are for the purpose of this literature review grouped into monetary, technical, infrastructural, and policy categories. The most often included attributes along with their concrete specification can be found in Table 2.2. Monetary, technical and infrastructural attributes are shown to significantly impact the EV purchasing decision. The effect of most policy attributes, except for tax reducing policies, which seem to be undoubtedly effective, stays ambiguous. Many of the attributes are highly affected by preference heterogeneity. A number of socio-economic and demographic characteristics, potentially explaining this preference heterogeneity, were uncovered. In the next sections effects of each attribute and individual characteristics of a respondent will be described in more details.

2.1 Monetary attributes

Monetary attributes were in some form incorporated into every reviewed study. Almost all studies dealt with purchase price attribute, indicating its importance as a factor influencing the choice of vehicle purchase. In general, electric vehicles are more costly than their conventional counterparts and it is suggested that their demand should remain low until pricing is competitive with conventional vehicles (Parsons *et al.* 2014). Undoubtedly, the most expensive component of BEVs is their batteries. It was found in Hidrue *et al.* (2011) that cost of batteries must drop significantly before electric vehicles will find a mass market. Therefore, they support investing into R & D in this area. Similarly, Lebeau *et al.* (2012) in their projections of EV up-take found that the speed of penetration is very sensitive to vehicle price, even though they foresaw the market share increase up to 15% for BEVs and up to 29% for PHEVs until 2030.

Contrary to this high up-front investment connected with EVs stay the associated savings on fuel costs, which might be even larger when the expected increase in gasoline prices occurs. However, high discount rates found in considered studies suggest that people are more sensitive to the money they pay upfront rather than to future savings (Horne *et al.* 2005). This gap might be potentially narrowed with electric vehicles with vehicle-to-grid (V2G) capability. V2G-EVs charge when electricity is cheap and discharge when expensive. For the power provided to the grid some cash back is provided to owners, which

Table 2.1: Overview of reviewed papers

Reference	Country	Year of data collection	Sample size	No. of tasks	Vehicle types included	Econometric model
Bunch *et al.* (1993)	US (California)	1991	717	5	GV, AFV, EV	NMNL
Golob *et al.* (1997)	US (California)	1994	2023	max 2	GV,CNG, EV, methanol	CL
Brownstone & Train (1998)	US (California)	1993	4747	1	GV, EV, CNG, methanol	standard logit, MXL, probit
Brownstone *et al.* (2000)	US (California)	1995	607	1	GV, EV, CNG, methanol	MNL, MXL
Ewing & Sarigöllü (2000)	Canada	NA	881	9	GV, AFV, EV	MNL
Dagsvik *et al.* (2002)	Norway	1995	662	15	GV, LPG, EV	rank-ordered logit, MXL
Batley *et al.* (2004)	UK	2001	179	16	AFV, CV	MNL, MXL
Horne *et al.* (2005)	Canada	2002-2003	886	4	GV, AFV, HEV, HV	MNL
Potoglou & Kanaroglou (2007)	Canada	2005	482	8	CV, HEV, AFV	NMNL
Mau *et al.* (2008)	Canada	2002	916+1019	18	CV, HEV, HV	MNL
Axsen *et al.* (2009)	Canada, US (California)	2002-2006	544+422	18	CV, HEV	MNL
Dagsvik & Liu (2009)	China	2001	100	15	GV, AFV	GEV rank-ordered models with fixed and random coefficients
Caulfield *et al.* (2010)	Ireland	2000	168	6	CV, HEV, AFV	MNL, NMNL
Erdem *et al.* (2010)	Turkey	2009	1974	1	CV, HEV	ordered probit
Hidrue *et al.* (2011)	US	2008-2009	3029	2	CV, 2 EVs	latent class
Mabit & Fosgerau (2011)	Denmark	2007	2146	12	CV, BEV, HEV, HV, biofuel	MXL
Qian & Soopramanien (2011)	China	2011	527	8	CV, BEV, HEV	MNL, NMNL

Notes: ASC - alternative-specific constant logit; NMNL - nested multinomial logit; CL - conditional logit; MXL - mixed logit; HB - Hierarchical Bayes; HCM - hybrid choice model; MNP - multinomial probit; MNL - multinomial logit; RUM - random utility maximization; RRM - random regret minimization

(Continued)

Table 2.1: Continued

Reference	Country	Year of data collection	Sample size	No. of tasks	Vehicle types included	Econometric model
Achtnicht (2012)	Germany	2007-2008	598	6	GV, BEV, HEV, HV, LPG/CNG, biofuel	standard logit, MXL
Achtnicht *et al.* (2012)	Germany	2007-2008	598	6	CV, BEV, HEV, HV, LPG/CNG, biofuel	standard logit
Hess *et al.* (2012)	US (California)	2008-2009	3274	8	CV, CNG, BEV, HEV, PHEV, biofuel	MNL, NMNL, cross-nested logit
Lebeau *et al.* (2012)	Belgium	2011	1197	10	CV, BEV, PHEV	HB
Link *et al.* (2012)	Austria	2011	274	8	CV, BEV, HEV	MNL
Shin *et al.* (2012)	South Korea	2009	250	NA	CV, BEV, HEV	multiple extreme value specifications
Ziegler (2012)	Germany	2012	598	6	CV, BEV, HEV, LPG/CNG, HV, biofuel	MNP
Bočkarjova *et al.* (2013)	Netherlands	2012	2977	6	CV, BEV, HEV	NMNL
Chorus *et al.* (2013)	Netherlands	2011	616	8	CV, HEV, PHEV, BEV, HV, flexifuel	models based in RUM as well as in RRM
Daziano (2013)	United States	2000	500	up to 15	CV, BEV, HEV	Bayesian CL
Daziano & Bolduc (2013)	Canada	2002	885	4	GV, AFV, HEV, HV	Bayesian HCM
Glerum *et al.* (2013)	Switzerland	2011	593	5	reference vehicle, similar Renault vehicle, similar electric vehicle	logit, HCM
Hackbarth & Madlener (2013)	Germany	2011	711	15	CV, CNG, BEV, HEV, PHEV, HV, biofuel	MNL, MXL
Jensen *et al.* (2013)	Denmark	2012	369	8	CV, EV	HCM, MXL
Stix & Hanappi (2013)	Austria	NA	714	9	CV, BEV, HEV, PHEV, CNG, biofuel	MXL
Hoen & Koetse (2014)	Netherlands	2011	1802	8	CV, LPG, BEV, PHEV, HV, biofuel	MNL, MXL

Notes: ASC - alternative-specific constant logit; NMNL - nested multinomial logit; CL - conditional logit; MXL - mixed logit; HB - Hierarchical Bayes; HCM - hybrid choice model; MNP - multinomial probit; MNL - multinomial logit; RUM - random utility maximization; RRM - random regret minimization

(Continued)

Table 2.1: Continued

Reference	Country	Year of data collection	Sample size	No. of tasks	Vehicle types included	Econometric model
Kim *et al.* (2014)	Netherlands	2012	726	16	CV, BEV	HCM
Koetse & Hoen (2014)	Netherlands	2011	940	8	CV, BEV, HEV, PHEV, HV, flexifuel	MNL, MXL
Parsons *et al.* (2014)	US	2009	3029	2	CV, 2 EVs	latent class
Tanaka *et al.* (2014)	US, Japan	2012	4202+4000	8	GV, BEV, PHEV	MXL
Axsen *et al.* (2015)	Canada	2013	1754	6	CV, BEV, HEV, PHEV	latent class, MNL
Dumortier *et al.* (2015)	US	2013	1499+1260	1	GV, BEV, HEV, PHEV	MNL, rank-ordered logit
Helveston *et al.* (2015)	US, China	2012-2013	384+572	15	CV, BEV, HEV, PHEV	MNL, MXL
Mabit *et al.* (2015)	Denmark	2007-2008	2093	4 or 8	CV, BEV, HEV, bio-diesel	MNL, HCM
Shin *et al.* (2015)	South Korea	2012	633	6	CV, BEV, HEV	multiple probit
Ščasný *et al.* (2015)	Poland	2014	8	CV, BEV, HEV, PHEV	MNL, MXL	
Valeri & Danielis (2015)	Italy	2013	121	12	CV, LPG/CNG, HEV, BEV (owned and leased battery)	MNL, MXL
Bahamonde-Birke & Hanappi (2016)	Austria	2013	1449	9	CV, BEV, HEV, PHEV	MNL, HCM
Cartenì *et al.* (2016)	Italy	NA	611	8	CV, EV	binomial logit
Hackbarth & Madlener (2016)	Germany	2011	711	15	CV, LPG/CNG, BEV, HEV, PHEV, HV, biofuel	MNL, latent class
Rasouli & Timmermans (2016)	Netherlands	2012	726	16	CV, BEV	MXL
Rudolph (2016)	Germany	2013	875	8	CV, BEV, PHEV, HV	MXL
Valeri & Cherchi (2016)	Italy	2013	121	12	CV, LPG/CNG, HEV, BEV (owned and leased battery)	MXL, HCM
Sheldon *et al.* (2017)	US	2013	1261	NA	GV, BEV, PHEV	MXL, ASC logit, latent class

Notes: ASC - alternative-specific constant logit; NMNL - nested multinomial logit; CL - conditional logit; MXL - mixed logit; HB - Hierarchical Bayes; HCM - hybrid choice model; MNP - multinomial probit; MNL - multinomial logit; RUM - random utility maximization; RRM - random regret minimization

Table 2.2: Overview of studied attributes

Attribute	Specification	Reference
Purchase price	Price	All in Table 2.1, except Erdem *et al.* (2010) and Caulfield *et al.* (2010)
Operating costs	Fuel cost per time period	Hess *et al.* (2012); Rudolph (2016); Dumortier *et al.* (2015) (also fuel cost savings); Axsen *et al.* (2015); Mau *et al.* (2008); Axsen *et al.* (2009); Potoglou & Kanaroglou (2007); Daziano (2013); Ewing & Sarigöllü (2000) (combined with parking costs); Horne *et al.* (2005); Link *et al.* (2012); Qian & Soopramanien (2011); Stix & Hanappi (2013)
	Fuel cost per distance travelled	Batley *et al.* (2004); Bunch *et al.* (1993); Brownstone & Train (1998); Brownstone *et al.* (2000); Golob *et al.* (1997); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Achtnicht *et al.* (2012); Bočkarjova *et al.* (2013); Jensen *et al.* (2013); Bahamonde-Birke & Hanappi (2016); Glerum *et al.* (2013); Sheldon *et al.* (2017); Shin *et al.* (2012); Shin *et al.* (2015); Helveston *et al.* (2015); Lebeau *et al.* (2012); Link *et al.* (2012) Ziegler (2012); Achtnicht (2012)
	Fuel cost per gallon (equivalent)	Parsons *et al.* (2014); Hidrue *et al.* (2011)
	Fuel cost relative to CV	Caulfield *et al.* (2010); Rasouli & Timmermans (2016); Kim *et al.* (2014); Tanaka *et al.* (2014)
	Maitenance cost	Hess *et al.* (2012); Bahamonde-Birke & Hanappi (2016); Glerum *et al.* (2013); Shin *et al.* (2012); Shin *et al.* (2015); Potoglou & Kanaroglou (2007) ; Ewing & Sarigöllü (2000); Stix & Hanappi (2013)
	Combined operating costs	Valeri & Danielis (2015); Valeri & Cherchi (2016); Mabit & Fosgerau (2011); Mabit *et al.* (2015); Daziano & Bolduc (2013); Lebeau *et al.* (2012) (excluding fuel costs); Mabit & Fosgerau (2011); Hoen & Koetse (2014)
	Personal monthly contribution	Koetse & Hoen (2014) (company car drivers)
	Total monthly cost of ownership	Dumortier *et al.* (2015)
	Battery lease costs	Glerum *et al.* (2013)
Driving range	Range after full charge/ refill	Batley *et al.* (2004); Bahamonde-Birke & Hanappi (2016); Bunch *et al.* (1993); Brownstone & Train (1998); Brownstone *et al.* (2000); Dagsvik *et al.* (2002); Daziano (2013); Dumortier *et al.* (2015); Ewing & Sarigöllü (2000); Golob *et al.* (1997); Chorus *et al.* (2013); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Helveston *et al.* (2015); Hidrue *et al.* (2011); Hoen & Koetse (2014); Jensen *et al.* (2013); Koetse & Hoen (2014); Kim *et al.* (2014); Lebeau *et al.* (2012); Link *et al.* (2012); Mabit & Fosgerau (2011); Mabit *et al.* (2015); Mau *et al.* (2008); Parsons *et al.* (2014); Qian & Soopramanien (2011); Stix & Hanappi (2013); Sheldon *et al.* (2017); Tanaka *et al.* (2014); Rasouli & Timmermans (2016); Valeri & Danielis (2015); Valeri & Cherchi (2016); Insignificant: Hess *et al.* (2012)
	Maximum/minimum range	Bočkarjova *et al.* (2013)
	All-electric range	Insignificant: Axsen *et al.* (2015); Helveston *et al.* (2015)
Refuelling/recharging	Time to full charge	Axsen *et al.* (2015); Bočkarjova *et al.* (2013); Chorus *et al.* (2013); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Hoen & Koetse (2014); Koetse & Hoen (2014); Kim *et al.* (2014); Lebeau *et al.* (2012); Link *et al.* (2012); Rasouli & Timmermans (2016)
	Time to 50 miles driving range	Hidrue *et al.* (2011); Parsons *et al.* (2014)
	Home recharging time	Brownstone & Train (1998)
	On-site recharging time	Golob *et al.* (1997)
	Service station recharging time	Brownstone & Train (1998); Golob *et al.* (1997)
	Refuelling frequency	Mabit & Fosgerau (2011)
Performance	Low/medium/high	Daziano (2013)
Engine power	Horsepower	Achtnicht (2012); Achtnicht *et al.* (2012); Axsen *et al.* (2009); Bahamonde-Birke & Hanappi (2016); Dagsvik & Liu (2009); Daziano & Bolduc (2013); Horne *et al.* (2005); Link *et al.* (2012); Ziegler (2012)

(Continued)

Table 2.2: Continued

Attribute	Specification	Reference
Fuel efficiency	Miles per gallon (equivalent)	Hess *et al.* (2012); Dumortier *et al.* (2015); Helveston *et al.* (2015);Brownstone & Train (1998); Brownstone *et al.* (2000)
	l/ 100 km	Dagsvik & Liu (2009); Dagsvik *et al.* (2002)
Acceleration	Time from 0 to 60 miles/hour (sec)	Helveston *et al.* (2015); Hess *et al.* (2012)
	Time from 0 to 30 miles/hour (sec)	Brownstone & Train (1998); Brownstone *et al.* (2000)
	Time from 0–100 km/h	Helveston *et al.* (2015); Hidrue *et al.* (2011); Potoglou & Kanaroglou (2007); Valeri & Danielis (2015); Mabit *et al.* (2015); Insignificant: Mabit & Fosgerau (2011)
	Relative to conventional gasoline car	Bunch *et al.* (1993); Ewing & Sarigöllü (2000); Parsons *et al.* (2014)
Maximum speed	Speed (km/h or miles/h)	Batley *et al.* (2004); Brownstone & Train (1998); Brownstone *et al.* (2000); Dagsvik *et al.* (2002); Kim *et al.* (2014); Lebeau *et al.* (2012); Rasouli & Timmermans (2016)
Vehicle size	Number of seats	Dagsvik & Liu (2009)
Cargo capacity		Golob *et al.* (1997)
Luggage space		Brownstone & Train (1998)
Fast charging capability		Helveston *et al.* (2015)
CO2 emissions	g CO2 per km	Caulfield *et al.* (2010); Achtnicht (2012); Achtnicht *et al.* (2012); Jensen *et al.* (2013); Link *et al.* (2012); Ziegler (2012)
	Number on a scale	Batley *et al.* (2004)
	Percentage relative to reference vehicle	Axsen *et al.* (2009); Brownstone & Train (1998); Brownstone *et al.* (2000); Bunch *et al.* (1993); Daziano & Bolduc (2013); Golob *et al.* (1997); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Hidrue *et al.* (2011); Parsons *et al.* (2014); Potoglou & Kanaroglou (2007); Tanaka *et al.* (2014)
	Percentage relative to ZEV	Ewing & Sarigöllü (2000)
Environmental performance	Ecoscore	Lebeau *et al.* (2012)
Charging availability	Distance from home to charging station	Kim *et al.* (2014); Rasouli & Timmermans (2016); Rudolph (2016); Valeri & Cherchi (2016); Insignificant: Valeri & Danielis (2015)
	Percentage share of service stations	Achtnicht (2012); Achtnicht *et al.* (2012); Batley *et al.* (2004); Bunch *et al.* (1993); Daziano & Bolduc (2013); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Horne *et al.* (2005); Lebeau *et al.* (2012); Mau *et al.* (2008); Potoglou & Kanaroglou (2007); Qian & Soopramanien (2011); Shin *et al.* (2012); Shin *et al.* (2015); Tanaka *et al.* (2014); Ziegler (2012)
	Percentage relative to gasoline car	Brownstone & Train (1998); Golob *et al.* (1997)
	Presence in differet areas	Jensen *et al.* (2013); Insignificant: Hess *et al.* (2012)
	Detour to purchase alternative fuel	Caulfield *et al.* (2010)
	Detour time than to gas station	Bočkarjova *et al.* (2013); Chorus *et al.* (2013); Hoen & Koetse (2014); Koetse & Hoen (2014)
	Low/medium/high	Bahamonde-Birke & Hanappi (2016); Stix & Hanappi (2013)
	Home plug-in construction fee	Tanaka *et al.* (2014)
Brand		Lebeau *et al.* (2012)
	Country origin of brand	Helveston *et al.* (2015)
	Numer of brands available	Chorus *et al.* (2013); Hoen & Koetse (2014); Koetse & Hoen (2014)
Warranty	Period/range covered by warranty	Mau *et al.* (2008)
	Battery life	Insignificant: Jensen *et al.* (2013)

might make this type of EVs more attractive to potential buyers. As found in Parsons *et al.* (2014) this benefit may be exploited the most when power aggregators operate on pay-as-you-go basis or provide consumers with upfront discounts on the price of EVs. Imposing fixed requirements on participants might cause the implicit inconvenience costs to override the potential benefits.

Associated with the monetary costs are financial incentives that seem to be an important factor in motivating people toward these new vehicle technologies. As for one example, in their study Potoglou & Kanaroglou (2007) show that monetary costs and purchase tax relief could encourage households to adopt an alternatively fuelled vehicle (AFV). These incentives will be discussed more deeply in Section 2.4. In what follows monetary attributes, namely purchase price, operating and battery costs, and total cost of ownership, will be elaborated and the most important/ interesting findings from the considered studies will be included.

2.1.1 Purchase price

Purchase price as an attribute was included in almost every reviewed study analysing stated preferences for EVs. It was not directly included as an attribute only in a study conducted by Erdem *et al.* (2010), who asked respondents to rate their WTP choosing among 7 classes of price premiums and then estimating the gathered data using an ordered probit model, and in a study led by Caulfield *et al.* (2010), who examined impacts of fuel costs, vehicle registration tax rates and CO2 emissions on vehicle purchasing decisions. They, however, found that those with preference for hybrid electric vehicles put a greater emphasis on vehicle price as a factor effecting car purchasing decisions compared to those who prefer conventional or alternatively fuelled vehicles.

In many studies the price attribute levels were derived from a price of a reference vehicle, hence customized for every respondent. Utilizing this pivotal design made the presented levels more realistic. Not surprisingly, in all studies that incorporated this attribute, purchase price was found to have a highly significant and negative effect. Moreover, demand for AFVs was found much more sensitive to purchase price than demand for conventional vehicles in Batley *et al.* (2004) and this sensitivity increased when the price of electric vehicles was much higher than the price of conventional ones (Rasouli & Timmermans 2016).

Except for few studies, the effect of price was examined as a linear relationship. As for the exceptions, for example, Mabit & Fosgerau (2011) directly incorporated a value function for the price attribute in their utility specification, which allowed the marginal utility of price to depend on whether the price of an alternative is above or below the price of the reference vehicle, Ziegler (2012) logarithmized the price and Link *et al.* (2012) used square root of the price to account for possible non-linearities.

2.1.2 Operating cost

Operating costs were also incorporated in almost every considered study, although their specifications differed. Most studies chose fuel cost as the attribute — as cost per distance: per mile (Batley *et al.* 2004), per km (Jensen *et al.* 2013) or 100 km (Hackbarth & Madlener 2016); as cost per time period: per year (Rudolph 2016), per month (Daziano 2013) or per week (Axsen *et al.* 2015); as cost per gallon or gallon equivalent (Parsons *et al.* 2014); or as cost of electricity relative to gas (Kim *et al.* 2014). In some cases the fuel cost was similarly to the purchase price attribute pivoted around costs related to the reference vehicle stated by the respondent, again making the choices more realistic (Axsen *et al.* 2015; Mau *et al.* 2008).

Some studies also included regular maintenance costs as separate attribute (Glerum *et al.* 2013; Hess *et al.* 2012) or grouped it with fuel costs in a combined (annual) operation cost attribute (Mabit *et al.* 2015; Valeri & Danielis 2015). As would be expected, operating costs are negatively associated with the decision to purchase a car. Since electric costs are on general connected with lower maintenance costs, this gives EVs the one clear-cut advantage over conventional vehicles (Beggs *et al.* 1981). In addition, Jensen *et al.* (2013) found that the marginal utility of fuel costs is much higher for electric vehicles than it is for conventional ones. This advantage of EVs is, however, not appropriately valued, as many studies show high associated discount rates of average consumers, in the range of 20% to 25% (Horne *et al.* 2005; Mau *et al.* 2008). These values might be even higher, around 50%, in the case of more uncertain V2G vehicles (Parsons *et al.* 2014).

2.1.3 Battery cost

Typically battery costs are incorporated into the purchase price of electric vehicles, but some studies directly examined the effect of battery leasing instead of its one-time purchase. Glerum *et al.* (2013) studied such business model which enabled leasing a battery for a specific monthly battery lease cost. Similar to other costs, this cost has a negative effect on the electric vehicle choice, while individuals with positive attitude towards leasing are less affected by a change in this rent. Option with leased battery was also included in Valeri & Danielis (2015), who showed that an electric vehicle with leased battery was less preferred than an electric vehicle with owned battery. They, however, did not disentangle the effect of fuel type from the brand effect, so the result might be brand, model and type related.

While Hackbarth & Madlener (2013) studied the effect of battery-leasing contracts only in their market share simulation by incorporating the monthly battery lease rent as additional fuel cost, pointing to a disability of these contracts to significantly push the demand for EVs. Fixed monthly battery lease payments, however, might be evaluated differently than increase in fuel cost, mainly due to their potential benefit as risk mitigation measure. This benefit might be the greatest, when considering V2G vehicles, batteries of which have shorter life expectancy due to increased cycling of the battery and hence are associated with higher effective battery costs (Parsons *et al.* 2014).

2.1.4 Total cost of ownership

As already mentioned, electricity powered vehicles are associated with high upfront investment, mainly due to high cost of batteries, and consequent fuel expenditure savings during the life time of the vehicle. As results in Dumortier *et al.* (2015) suggest, consumers may have difficulties comparing the value of fuel expenditure savings to the vehicle price in a meaningful way and as such find the information about fuel savings statistically insignificant. When they examine the effect of adding information about total cost of ownership, they find that it increases the preference of small/ mid-sized car consumers towards conventional hybrid, plug-in hybrid, or battery electric vehicles. However, no such effect is found for consumers of small sport utility vehicles.

In a similar fashion, Bočkarjova *et al.* (2013) utilized a generalized cost of ownership approach, as it became apparent from their pilot testing that respondents were not considering the shown attributes one by one, but rather were clustering the attributes in order to calculate costs and benefits associated with vehicle ownership when making the decision. The generalized annual monetary costs variable was unsurprisingly found to significantly negatively affect the vehicle choice. Kochhan & Hörner (2015) also attempt to estimate the total cost of ownership of electric vehicles. When they compare it with the estimated willingness-to-pay, they find that the WTP is significantly lower than the costs. They propose that in the case of Singapore, this gap can potentially be narrowed by changing regulatory parameters such as tax reductions. Modifying technical specifications like the battery costs does not seem yet to have the potential to equalize the total costs with WTP.

2.2 Technical attributes

Besides monetary attributes discussed above, many technical vehicle features affect the car purchase decision and, therefore, are incorporated into the choice experiments of almost every reviewed study. The concrete technical attributes chosen and their specification, however, differ among papers. In what follows, the attributes that appeared the most often are discussed, and the most significant or interesting results regarding each of them are presented. Undoubtedly, the most important functional attribute of electric vehicles are their relatively limited driving range and associated relatively long recharging time. Therefore, these two attributes are discussed in more detail.

2.2.1 Driving range

A relatively short driving range compared to conventional vehicles is justifiably considered one of the biggest limitations of EVs, hampering their market uptake, and as suggested by Dagsvik *et al.* (2002) they will not become fully competitive unless the limited driving range increases substantially. Therefore many studies included this attribute in their choice experiments. The majority of them studied driving range of a vehicle after full charge or refill, while a couple focused solely on all-electric driving range (Axsen *et al.* 2015; Helveston *et al.* 2015). Only Bočkarjova *et al.* (2013) concentrated on both maximum and minimum range depending on outside circumstances, as the potential driving range of an EV depends not only on battery capacity, but also on outside temperatures or other factors affecting the wearing of batteries such as switching on air conditioning.

In most reviewed studies driving range attribute enters the utility function in linear form, although in some studies in logarithmic transformation (Daziano 2013; Hackbarth & Madlener 2016; Hess *et al.* 2012; Link *et al.* 2012). Possible non-linearity of this attribute was studied by incorporating the quadratic term into the utility function (Brownstone *et al.* 2000; Bunch *et al.* 1993; Sheldon *et al.* 2017). This term was found to be significant and negative, suggesting diminishing marginal utility as the maximum driving range increases. In general the effect of driving range on EV purchase decisions is found to be statistically significant and positive. However, for short driving range levels of 30 to 60 miles the effect was found insignificant (Hess *et al.* 2012). Axsen *et al.* (2015) the all-electric driving range of plug-in hybrid and battery electric vehicles was also found insignificant, possibly indicating not enough variety of range levels in the choice experiment or the fact that respondents found it hard to place a value on a unit of electric driving range with little or no previous experience with electric vehicles.

While for the limited range of 100km the effect was found even significantly negative (Kim *et al.* 2014; Rasouli & Timmermans 2016). This indicates that limited driving range is indeed considered an important barrier to the adoption of electric vehicles, and that consumers value and are willing to pay for the improvement in this attribute. The estimated average WTP values were found in the range from $35 to $80 for an extra mile added to driving range (Golob *et al.* 1997; Hidrue *et al.* 2011). Similar value of about £35 was uncovered by Axsen *et al.* (2015) in the UK settings. The incremental WTP was, however, found to be decreasing at higher distances (Hidrue *et al.* 2011), e.g. Koetse & Hoen (2014) pointed that the marginal WTP values declined from €1.44, when the change from 75km to 250km in max driving range was studied, to €1.2 per 1km when the change was from 75km to 350km.

As expected the marginal utility for driving range was found to be much higher and more important for battery electric vehicles than for conventional vehicles (Achtnicht *et al.* 2012; Hackbarth & Madlener 2013), which can be explained by the large difference in range between these two car types and the 'range anxiety' associated with the former. Valeri & Danielis (2015) presented the comparison indicating that WTP for a 1km increase in range as a generic attribute equalled to €7.47, while for BEVs the range specific attribute corresponded to WTP of €50.4 per a 1km increase. Similarly, Hackbarth & Madlener (2013) found WTP values of €16.21 and €32.76 per km for the BEVs priced below and above €20,000, respectively, and values of €8.32 and €16.82 per km for the non-BEVs priced below and above €20,000, respectively. Overall, the WTP values for BEVs' range are similar to those stated above.

High preference heterogeneity for battery electric vehicles was uncovered by Rasouli & Timmermans (2016) when the range considered was up to 100km, levels similar to most currently available BEVs. This indicates that there are some consumers truly interested in buying an electric car, regardless of its limitations, whereas others are likely to be discouraged. This heterogeneity seems to vanish with higher values, when the range reaches 400km. The importance of increased range of BEVs was also supported in Hackbarth & Madlener (2013), who in their market simulations found that an increase in the BEVs' range to a level comparable with all other vehicles (range of about 750km) had the same impact as a proposed multiple measures policy intervention package. Unfortunately, as suggested in their later paper, German car buyers were not found to be willing to pay the necessary amounts of money for the increase in battery capacity, even if they generally seem to like BEVs (Hackbarth & Madlener 2016).

Furthermore, regarding the heterogeneity in preferences it was found by Hoen & Koetse (2014) that when annual mileage of a respondent increases, the WTP for driving range also increases substantially. It might be believed that when drivers gain experience with BEVs, their 'range anxiety' might be relaxed. However, Jensen *et al.* (2013) found the exact opposite, i.e. the importance attached to driving range for the BEV almost doubled after an individual had tried the car for a period of three months. The WTP value for 1km increase in driving range increased from €65 to €134 for single car households. This possibly indicates that individual concerns were being met by the characteristics of EVs currently available in the market. This effect was, however, milder for households with multiple cars, as they could possibly rely on the other car when the need for a longer trip arises. The associated WTP values increased from €46 to €84 per km after the trial period. This 'multi or hybrid household hypothesis' was first supported by Kurani *et al.* (1996).

2.2.2 Refuelling/recharging time

Associated with the limited driving range of current electric vehicles is the substantially longer time required to charge the batteries compared to refuelling conventional vehicles, which in general takes only a few minutes. Recharging time of EVs greatly depends on the power of the charging station and the capacity of batteries. Generally, two charging modes can be distinguished, although other charging configurations can be found as well — slow charging where the car is usually parked either at home or at work, which takes around 6-8 hours to charge fully, and fast charging in specific charging stations, which can recharge the battery within 15-30 minutes. Since it certainly is an important attribute affecting the decision to purchase an EV, many studies included this attribute in their choice experiments. Most studies studied recharging/refuelling time as a generic attribute (Chorus *et al.* 2013; Hackbarth & Madlener 2013; Lebeau *et al.* 2012), entering the utility function linearly. Hackbarth & Madlener (2016) used a logarithmic specification, while Link *et al.* (2012) studied this attribute squared.

Some studies made this attribute specific to plug-in electric vehicles, either specified as time to full charge (Kim *et al.* 2014; Hoen & Koetse 2014), as recharge time for 50 miles of driving range (Hidrue *et al.* 2011), or as refuelling frequency (Mabit & Fosgerau 2011). Only Bočkarjova *et al.* (2013) and Golob *et al.* (1997) specifically distinguished between slow and fast charging. In all the studies that included this attribute, however, its effect was found to be significant and negative with regard to the decision to choose an EV. Ewing & Sarigöllü (2000) found the refuelling rate to be significant and negative only at long refuelling time of 300 minutes, possibly indicating that consumers are being discouraged only by significantly long time required to recharge their vehicles. However, as found in Parsons *et al.* (2014) consumers may exaggerate the disutility associated with longer recharging times, as they in general lack awareness of how many hours their cars are parked, and they overvalue the flexibility in car use.

Regarding heterogeneity in preferences there was found none associated with higher battery recharge time, but there exist significant heterogeneity for the shorter time categories (Rasouli & Timmermans 2016). This might indicate that only a few people are discouraged with relatively small additional time spent recharging batteries, while a substantial increase possibly discourages all consumers. Moreover, unsurprisingly, battery recharging time was found to be twice as important in the case of battery electric vehicles compared to plug-in hybrid ones (Hackbarth & Madlener 2013). In the case of PHEVs, only significant was a substantial drop from 3 hours of charging time to 20 minutes, possibly indicating that recharging time is not that important attribute for PHEVs as it is for pure battery electric vehicles (Koetse & Hoen 2014).

2.2.3 Performance

Performance is usually incorporated as acceleration time, fuel efficiency, engine power or maximum speed, while Daziano (2013) combined max speed and acceleration, and specified performance in general as either low, medium, or high. Fuel efficiency is indirectly correlated with operational costs and if this attribute is measured as % relative to CV, then GHG emissions and operational costs are directly correlated. Moreover, when fuel efficiency is specified as g CO2 per km then this attribute is also directly correlated with GHG emissions.

Overall, as would be expected, consumers were found to prefer better performance of any vehicle. In general these attribute enter the specified utility function linearly, although Link *et al.* (2012) used square root transformation of engine power. Mabit & Fosgerau (2011) found acceleration as generic attribute not significant, while Valeri & Danielis (2015) found even acceleration specifically tested for BEVs to be insignificant, which might be surprising as BEVs are being promoted in the non-scientific literature for their acceleration performance.

Possible explanations for this insignificance may lie in the lack of experience with BEVs, so that respondents cannot assign proper values to this attribute, or it might be rooted in the high preference heterogeneity among respondents, whose responses may be averaged out. Acceleration was found to be valued more by middle aged males living in single households (Mabit & Fosgerau 2011; Mabit *et al.* 2015), while it was found significantly less important for female respondents (Potoglou & Kanaroglou 2007). As for the top speed variable, Rasouli & Timmermans (2016) uncovered that respondents' preferences differ more widely if the top speed is lower, between 80km/h to 120km/h.

2.2.4 GHG emissions

Although vehicle performance characteristics are critical to the choice of vehicle, it was found that consumers also value environmental impact of a car (Ewing & Sarigöllü 2000). Bočkarjova *et al.* (2013) even uncovered, that environmental costs of CO2 reductions are valued far above the market average, but continued that this aspect affects choices of electric vehicles only at a later stage of their adoption in the market. Achtnicht (2012) found that consideration of this aspect varied heavily across the sampled population. In particular, women under 45 years with higher education valued this attribute significantly more. Moreover, unsurprisingly CO2 emissions were valued higher for respondents with high environmental awareness (Achtnicht *et al.* 2012; Hackbarth & Madlener 2013).

There is, however, an underlying issue associated with incorporating environmental attributes into stated choice experiments, namely that respondents might choose a socially desire option in the hypothetical scenario, which might not be reflected in real-life conditions. Nevertheless, not negligible number of studies included this attribute in their choice experiments, mostly as percentage relative to a conventional gasoline vehicle (e.g. Hidrue *et al.* 2011; Parsons *et al.* 2014) or in absolute terms as g of CO2 emissions per km (e.g. Achtnicht 2012; Jensen *et al.* 2013), while Batley *et al.* (2004) presented this attribute as a number on a scale. In most of the reviewed papers this attribute was studied linearly, although in logarithmic specification in Hackbarth & Madlener (2016). Possible nonlinearity was studied in Bunch *et al.* (1993) by including quadratic term, finding this term significant and positive. This suggests diminishing disutility associated with higher emission levels.

2.2.5 Brand and model diversity

Diversity in the choice between electric vehicles was found to increase the probability of choosing an EV (Chorus *et al.* 2013; Hoen & Koetse 2014). Koetse & Hoen (2014) valued the associated WTP of a change from 1 to 10 models available to be €71, change from 1 to 50 to account for €91, and from 1 to 200 to reach €123. This might indicate that with higher number of brands and models available in the market requirement about a car specific to a consumer are more likely to be met, or it can suggest that respondents associate greater model diversity with electric vehicle market maturity, and hence the associated uncertainty with EVs decreases. Moreover, Helveston *et al.* (2015) studied the effect of countries as an origin of a brand and they found that these country preferences differ among respondents from the US and China. Valeri & Danielis (2015) directly labelled their vehicle options with the name of a brand and model, but they did not disentangle this brand effect from the fuel powertrain effect.

2.2.6 Warranty

There is a lot of uncertainty regarding the life of BEVs' batteries, the wearing of which might be accelerated by frequent recharging or by utilizing additional technologies of a vehicle, such as air conditioning. This uncertainty might be mitigated by proper warranty coverage; hence a couple of reviewed papers studied this effect on the EV purchase choice decisions, although with indecisive results. Mau *et al.* (2008) found it to positively affect the adoption of electric vehicles, while Jensen *et al.* (2013) found the effect of battery life to be insignificant both before and after a three-month trial period with an electric vehicle.

2.3 Charging stations infrastructure

The limited driving range of electric vehicles can be to some extent counterbalanced by a sufficiently dense charging infrastructure, although Bahamonde-Birke & Hanappi (2016) point towards the existence of certain reliability thresholds, below which the effect stays insignificant. Ito *et al.* (2013) found that infrastructural development can be efficient only when sales of BEVs exceed 5.63% of all new vehicle sales. Nevertheless, charging infrastructure is undoubtedly important when attempting to enhance the market uptake of electric vehicles and hence many studies studied the effect of this attribute, although relying on different specifications. Most studies used the percentage share of all service stations or relative to gasoline ones; other chose the distance from home to the closest charging station (Kim *et al.* 2014; Valeri & Cherchi 2016), while some relied on detour (defined as additional distance or time) to purchase alternative fuel (Caulfield *et al.* 2010; Chorus *et al.* 2013). Other specification included presence of a charging station in different areas, e.g. at home, at work or in shopping malls, or defined charging availability in general as low, medium, or high.

In most studies a higher availability of charging infrastructure has a significant positive effect on the choice of electric cars (Rudolph 2016), although Valeri & Danielis (2015) found the refuelling distance attribute insignificant for both BEVs and HEVs. Most studies considered this attribute to enter the specific utility function linearly, possibly in logarithmic specification (Hackbarth & Madlener 2016). Incorporating the term squared pointed towards diminishing marginal utility (Achtnicht 2012; Bunch *et al.* 1993). Fuel availability was unsurprisingly found more important for battery electric vehicles than for other AFVs, and the failure to expand the charging stations might significantly hinder the wider adoption of BEVs (Achtnicht 2012). The installation of which, however, brings along high upfront investments, uncertainty about future returns depending on the market penetration of electric vehicles, and associated legal issues concerning property rights. The results of the studies, however, lead to the fact that consumers are willing to pay for improvements in this attribute. Koetse & Hoen (2014) found the WTP for a drop in detour time from 30 to 5 minutes to be €161, and from 30 min to no detour time to reach €219.

A certain limitation of the reviewed studies may lie in the fact that most did not differentiate between slow charging posts and fast charging stations, which are used for different purposes. While public slow charging posts are intended for home parking, workplaces or shopping malls, where a car is expected to be parked for longer periods, fast charging stations are designed mainly for highway location to support longer trips or serve in cases of emergency. Interestingly, as previous research showed that charging station infrastructure is seldom used and the car is more likely to be charged at home (Golob *et al.* 1997), the improved infrastructure may help mainly in reducing the uneasiness of 'range anxiety'. Nevertheless, Hackbarth & Madlener (2016) stated that individuals would accept considerable markups on the electricity price for a large-scale fast charging infrastructure. In this aspect, Ščasný *et al.* (2015) pointed towards high non-linearities in preferences of respondents for fast-mode recharging, as in their study the only significant was found the effect of very high fast charging availability, at almost all public stations.

2.4 Policy attributes

This group of attributes includes various policy instruments used for promoting higher market uptake of electric vehicles. Several incentives were tested in the reviewed studies. In Table 2.3 an overview of their findings can be found. If the parameter for a given policy attribute turns out to be significant, then the policy itself can be potentially considered as effective.

Concerning one-time price reductions, reduction or exemption of purchase tax is found to be significant in all studies that incorporated it, whereas direct purchase price reduction is significant only in 4 out of 7 cases. This phenomenon can be seen the best when taking into account the study conducted by Hess *et al.* (2012), in which they found tax reduction incentive positive and significant, while reduction in purchase price was not significant. Both these reductions were set to the same amount of $1,000. In connection with the one-time price reducing policies some studies tested the effect of reduction in vehicle registration tax. Generally this effect was found to be positive and significant, although Caulfield *et al.* (2010) found mixed results — ineffective for hybrid electric vehicles and effective for cars run on any alternative to petrol or diesel in general. Hackbarth & Madlener (2013) found no vehicle tax incentive to be valued almost twice as highly as the possibility of bus lane access and free parking.

Regarding policies reducing usage costs, those targeting taxation all turned out significant, regardless of whether they favored 'cleaner' vehicles, e.g. reduction in road tax or CO2 tax, or whether they put burden on conventional vehicles, e.g. tax on fuel costs for these vehicles. Results of Daziano & Bolduc (2013) find the fossil fuel taxation the most effective in increasing the low-emission vehicles market penetration. Reducing toll was, however, found insignificant in Hess *et al.* (2012). This might be caused by the fact that consumers generally tend to perceive taxes differently from other expenses. Results for another usage costs reduction policy —- free parking incentive —- remain ambiguous. Slightly less than half of the reviewed studies that included this attribute found its effect significant, while the rest points towards its insignificance.

Nevertheless, some studies point towards the overall inefficiency of pricing strategies in significantly altering the relative market power between the conventional and alternatively fuelled vehicles in favor of AFVs (Valeri & Danielis 2015). Axsen *et al.* (2009) also suggests that targeting non-financial attributes may result in more efficient outcomes than financial strategies. As for the non-financial attributes themselves, the effect of free public transportation incentive for the electric vehicle owner or their family members was found to be insignificant in all the studies that incorporated it. In contrast, the impact of Annual Park and Ride subscription remained undecided – significant in one study and not significant in another. More studied was, however, the effect of giving EVs access to high-occupancy vehicle (HOV) or other special lanes. In 5 out of 11 studies that included this attribute it was found significant, although Sheldon *et al.* (2017) found this effect only for PHEVs.

Many reasons that might explain the conflicting findings and insignificance of non-financial incentives can be found. The place of respondent's residence matters. People living in areas without congested traffic may not value the access to HOV or express lanes as much as people who have to face heavy traffic regularly. In addition, people from places with no HOV lanes may experience difficulties when valuing this attribute. Also in less populated areas with less developed public transportation people might not be able to value its benefits appropriately. Moreover, the preference heterogeneity of different subgroups of population could result in the parameter insignificance when considering the average.

Table 2.3: Overview of policy attributes

Policy	Studied which found it to be effective	Studied which found it to be ineffective
One-time price reducing policies		
Direct purchase price subsidy	ZEV: Rudolph (2016); HEV: Mau *et al.* (2008); HEV: Valeri & Danielis (2015); Glerum *et al.* (2013)	Hackbarth & Madlener (2016); Hess *et al.* (2012); Qian & Soopramanien (2011)
Reduction/ exemption of purchase tax	Hess *et al.* (2012); Potoglou & Kanaroglou (2007)	
Reduction in vehicle registration tax	AFV: Caulfield *et al.* (2010); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016)	HEV: citetCaulfield2010
Usage costs reducing policies		
Reduction in road tax	Chorus *et al.* (2013); Hoen & Koetse (2014)	
Tax on fuel costs for ICV	ZEV: Rudolph (2016)	
CO2 tax	ZEV: Rudolph (2016)	
Reduced toll		Hess *et al.* (2012)
Free parking	ZEV: Rudolph (2016); Hackbarth & Madlener (2016); Koetse & Hoen (2014); Ščasný *et al.* (2015)	Chorus *et al.* (2013); Hess *et al.* (2012); Hoen & Koetse (2014); Potoglou & Kanaroglou (2007); Qian & Soopramanien (2011)
Charging infrastructure incentives		
Increase in availability of charging infrastructure for ZEV	ZEV: Rudolph (2016)	
Subsidies to support private charging stations	Bahamonde-Birke & Hanappi (2016)	
Non-financial incentives		
Annual Park and Ride subscription	Stix & Hanappi (2013)	Bahamonde-Birke & Hanappi (2016)
Free public transportation		Bahamonde-Birke & Hanappi (2016); Ščasný *et al.* (2015)
HOV/ express/ priority/ bus lane access	PHEV: Sheldon *et al.* (2017); Daziano & Bolduc (2013) Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Horne *et al.* (2005)	Chorus *et al.* (2013); Hess *et al.* (2012); Hoen & Koetse (2014); Koetse & Hoen (2014); Potoglou & Kanaroglou (2007); Qian & Soopramanien (2011)

Notes: HOV – high-occupancy vehicle; ICV – internal combustion engine vehicles; ZEV – zero emission vehicles

However, Hackbarth & Madlener (2013) raise doubts about the general effectiveness of policy incentives to propagate electric vehicles, as in their scenario analysis they find evidence that an increase in the fully electric driving range to a level comparable with all other car alternatives (750km of driving range for battery electric vehicles) has the same impact as would a multiple measures policy intervention package, consisting of exemption from vehicle circulation tax, bus lane access, free parking incentive, purchase premium of €5,000, 100% fuel availability, and recharging time of 5 min for BEVs. Similar results supporting improvements in vehicle performance characteristics rather than other incentives can be found in Ewing & Sarigöllü (2000). Therefore, they recommend government intervention in the form of industry subsidies in order to improve the performance of electric vehicles over direct consumer subsidies. This view is also backed in Bahamonde-Birke & Hanappi (2016), who find the best evidence for investment subsidies supporting private charging stations.

Moreover, policy instruments used to incentivize the substitution of conventional vehicles by their electrified alternatives might bring along the undesired rebound effect of households adding an electric vehicle to their car fleet, and hence increasing the total number of vehicles and worsening the overall energy ratio for transport (Rudolph 2016). Ewing & Sarigöllü (2000) state that government interventions, when resulting in a premature introduction of electric vehicles to the public, could result in destruction of the potential market. Except for redirecting expenses to improving the EVs' performance, they see a beneficial role of government in propagating EVs by guaranteeing the existence of a market by becoming one of the industry's first customers.

2.5 Heterogeneity of preferences

In the previous sections effects of many attributes and general preference for electric vehicles were found to be strongly dependent on individual characteristics of a respondent. In this section the focus is put on the impact of individual-specific variable on the overall preference for EVs. Among the reviewed studies their effect, however, remains ambiguous. Almost every individual-specific variable was found insignificant in at least one study. In Table 2.4 are, therefore, listed only studies, in which the considered variables turned out to be significant.

Table 2.4: Effects of observed heterogeneity on EV preference

Factors	Specific variable	Studies which found significant positive effect	Studies which found significant negative effect
Gender	Male	Rasouli & Timmermans (2016); Kim *et al.* (2014); Parsons *et al.* (2014); HEV: Erdem *et al.* (2010); HEV: Link *et al.* (2012); AFV: Stix & Hanappi (2013); Shin *et al.* (2015); Tanaka *et al.* (2014); HEV: Ziegler (2012)	Rasouli & Timmermans (2016); Dagsvik *et al.* (2002) Daziano & Bolduc (2013); Jensen *et al.* (2013); Mabit & Fosgerau (2011); Mabit *et al.* (2015); HEV: Caulfield *et al.* (2010); Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011); Link *et al.* (2012)
Age		Dagsvik *et al.* (2002); Daziano & Bolduc (2013); AFV: Batley *et al.* (2004); PHEV: Hackbarth & Madlener (2016); AFV: Caulfield *et al.* (2010); HEV: Link *et al.* (2012)	Bunch *et al.* (1993); Parsons *et al.* (2014); Cartenì *et al.* (2016); Dumortier *et al.* (2015); Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Achtnicht (2012); Bahamonde-Birke & Hanappi (2016); Hidrue *et al.* (2011); Qian & Soopramanien (2011); Ziegler (2012); AFV: Potoglou & Kanaroglou (2007); Link *et al.* (2012); Shin *et al.* (2015); Stix & Hanappi (2013); Tanaka *et al.* (2014) (US)
Education level		Bunch *et al.* (1993); Brownstone & Train (1998); Brownstone *et al.* (2000); PHEV: Dumortier *et al.* (2015); Non-monotonous: Rasouli & Timmermans (2016); Kim *et al.* (2014); Axsen *et al.* (2015); PHEV: Hackbarth & Madlener (2013); HEV: Erdem *et al.* (2010); Hidrue *et al.* (2011); HEV: Potoglou & Kanaroglou (2007); Stix & Hanappi (2013); Valeri & Cherchi (2016)	
	University	Daziano & Bolduc (2013); Tanaka *et al.* (2014) (US)	
Income		Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011); Rasouli & Timmermans (2016); AFV: Dagsvik & Liu (2009); HEV: Erdem *et al.* (2010); HEV: Caulfield *et al.* (2010); HEV: Link *et al.* (2012); Stix & Hanappi (2013)	Bunch *et al.* (1993); Helveston *et al.* (2015) (US); PHEV: Helveston *et al.* (2015) (US); Link *et al.* (2012)
Household		Axsen *et al.* (2015); Tanaka *et al.* (2014)	
	Household size	Qian & Soopramanien (2011)	
	Number of kids	Rasouli & Timmermans (2016); Kim *et al.* (2014); AFV: Batley *et al.* (2004); AFV: Stix & Hanappi (2013)	Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011); HEV: Link *et al.* (2012)
	Number of drivers		Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011)

Notes: HOV – high-occupancy vehicle; ICV – internal combustion engine vehicles; ZEV – zero emission vehicles

(Continued)

Table 2.4: Continued

Factors	Specific variable	Studies which found significant positive effect	Studies which found significant negative effect
Current car situation	Owning a car	Qian & Soopramanien (2011)	
	Number of household vehicles	Cartenì *et al.* (2016); Helveston *et al.* (2015) (Only in China); Jensen *et al.* (2013); Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011); Ziegler (2012); PHEV: Sheldon *et al.* (2017); Jensen *et al.* (2013); Insignificant: Bunch *et al.* (1993)	AFV: Batley *et al.* (2004); Dumortier *et al.* (2015)
	Mini or small	Jensen *et al.* (2013); HEV: Link *et al.* (2012)	
	Second-hand car	Jensen *et al.* (2013)	
	Owning a new technology car	Dumortier *et al.* (2015)	
	Engine size	HEV: Caulfield *et al.* (2010)	
Expected car	Mini or small, cheaper	Hackbarth & Madlener (2013); HEV: Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); Hidrue *et al.* (2011)	
	Larger, more expensive	PHEV: Hackbarth & Madlener (2016)	
	Station wagon		Brownstone & Train (1998); Brownstone *et al.* (2000)
	Sports car	Brownstone & Train (1998)	Brownstone *et al.* (2000)
	Sports utility vehicle	Brownstone & Train (1998); Brownstone *et al.* (2000)	Bunch *et al.* (1993)
	Compact pick up	Golob *et al.* (1997)	
	Truck		Brownstone & Train (1998); Brownstone *et al.* (2000); Golob *et al.* (1997)
	Van		Brownstone & Train (1998)
	Horsepower		Ziegler (2012)
	Driving range	Ziegler (2012)	
Environmental concern	Pro-environmental attitude	Kim *et al.* (2014); Axsen *et al.* (2015); Daziano & Bolduc (2013); Sheldon *et al.* (2017); AFV: Batley *et al.* (2004); Hackbarth & Madlener (2013); PHEV: Hackbarth & Madlener (2013); Hackbarth & Madlener (2016); PHEV: Hackbarth & Madlener (2016); Achtnicht (2012); Hidrue *et al.* (2011); Jensen *et al.* (2013); Bahamonde-Birke & Hanappi (2016); Ziegler (2012); Stix & Hanappi (2013)	
	Environment-oriented lifestyle	Axsen *et al.* (2015); Parsons *et al.* (2014)	
	Concern about global warming	HEV: Erdem *et al.* (2010)	
	Actively or passively concerned	Ewing & Sarigöllü (2000)	
	Positive perception about alternative energy sources	HEV: Erdem *et al.* (2010)	

Notes: HOV – high-occupancy vehicle; ICV – internal combustion engine vehicles; ZEV – zero emission vehicles

(Continued)

Table 2.4: Continued

Factors	Specific variable	Studies which found significant positive effect	Studies which found significant negative effect
Pro-innovation attitude		Kim *et al.* (2014); Hidrue *et al.* (2011); Bočkarjova *et al.* (2013)	HEV: Erdem *et al.* (2010)
	Liminal lifestyle	Axsen *et al.* (2015)	
	Buying new goods on the market	Parsons *et al.* (2014)	
	Early adopter	Sheldon *et al.* (2017)	
	Car as a status symbol	Helveston *et al.* (2015) (US)	Helveston *et al.* (2015) (China)
Risk lovers		HEV: Erdem *et al.* (2010)	
Technology-oriented lifestyle		Axsen *et al.* (2015); Hackbarth & Madlener (2016)	
Charging facilities	Charging at home	Parsons *et al.* (2014); Rasouli & Timmermans (2016); Hackbarth & Madlener (2013); Helveston *et al.* (2015) (China); Hidrue *et al.* (2011); Hoen & Koetse (2014); PHEV: Hackbarth & Madlener (2013); PHEV: Sheldon *et al.* (2017)	Batley *et al.* (2004)
	Fast charging at home	Axsen *et al.* (2015)	Valeri & Danielis (2015)
	Fast charging public station in respondent's community	Dumortier *et al.* (2015)	
Having a garage		Link *et al.* (2012)	Valeri & Danielis (2015); HEV: Link *et al.* (2012)
Parking at work		Sheldon *et al.* (2017)	
Living in urban area		AFV: Stix & Hanappi (2013)	
Countries and regions		Tanaka *et al.* (2014); Helveston *et al.* (2015)	
Travel patterns	Driving more than 100 miles/ day at least one day a month	Parsons *et al.* (2014)	ZEV: Rudolph (2016)
	Long distance trips	Valeri & Cherchi (2016)	
	Frequency of long trips	Cartenì *et al.* (2016); Hidrue *et al.* (2011); HEV: Link *et al.* (2012)	
	Annual mileage	Ziegler (2012) (expected mileage)	HEV: Achtnicht (2012); Hoen & Koetse (2014); Koetse & Hoen (2014)
	Daily mileage	Hackbarth & Madlener (2016); AFV: Stix & Hanappi (2013)	
	Percentage of city trips	Hackbarth & Madlener (2013)	
	Holding annual transit pass	ZEV: Rudolph (2016)	
	Frequency of using bicycle	ZEV: Rudolph (2016)	Sheldon *et al.* (2017)
	Frequency of using public transport	ZEV: Rudolph (2016)	Daziano & Bolduc (2013)
	Commute under 20 miles	Brownstone & Train (1998)	
	Commuting distance		Qian & Soopramanien (2011); HEV: Qian & Soopramanien (2011)
	Commuting frequency		PHEV: Hoen & Koetse (2014)
	Commuting time (minutes/ one way)		Ewing & Sarigöllü (2000)
	Commuting cost per week		Ewing & Sarigöllü (2000)
	Carpool user	Daziano & Bolduc (2013)	Valeri & Danielis (2015)
	Transit user	Daziano & Bolduc (2013)	
Car technology awareness		HEV: Erdem *et al.* (2010)	
Experience with EV	Trial period		Jensen *et al.* (2013)
Positive reviews		Rasouli & Timmermans (2016); Kim *et al.* (2014)	
Market share		HEV: Mau *et al.* (2008)	

Notes: HOV – high-occupancy vehicle; ICV – internal combustion engine vehicles; ZEV – zero emission vehicles

2.5.1 Socioeconomic and demographic characteristics

Although socioeconomic and demographic characteristics are included most often in choice studies, their effects on overall preference for electric vehicles remain undetermined. Most important socioeconomic and demographic variables include gender, age, education level, income, and household composition. Except for higher education level, which is clearly found to have a positive effect on EV preference, the effects of all other variables remain unclear, with supporting evidence for both cases. Their effects, either positive or negative, still vary within the relevant studies, mainly due to modelling choices. For example, Rasouli & Timmermans (2016) found the effect of gender to have opposite signs in two different models using the same dataset.

Moreover, some studies found an income effect, indicating that people with higher incomes are less price sensitive than the rest (Bahamonde-Birke & Hanappi 2016; Hess *et al.* 2012; Helveston *et al.* 2015; Mabit & Fosgerau 2011; Potoglou & Kanaroglou 2007; Valeri & Danielis 2015). Those intending to buy a cheaper car (Achtnicht 2012; Hackbarth & Madlener 2013) or used car (Hoen & Koetse 2014; Ščasný *et al.* 2015) also seem to be more price-sensitive. Moreover, those interested in the design of a car rather than in its practical aspects are found to be more affected by its price (Glerum *et al.* 2013).

Similarly, respondents with higher income put less emphasis on the operating costs (Valeri & Danielis 2015). This finding is also confirmed in Helveston *et al.* (2015) for US respondents, but they found the contrary for Chinese respondents. This might suggest that in China higher income buyers who can afford electric vehicles also value their operating cost savings more, potentially increasing attractiveness of electric vehicles.

2.5.2 Attitudinal and psychological factors

Still more and more studies incorporate factors from psychological theories in order to construct more comprehensive models with higher explanatory powers. The most important of these factors influencing the EV adoption is related to environmental concerns. These are found to have a positive impact on the preference for electric vehicles in all of the reviewed studies that incorporated them. The way how environmental concerns are measured, however, differs among studies. Most use indicators of pro-environmental attitude (e.g. Daziano 2013) or environmentally friendly behavior (e.g. Axsen *et al.* 2015), while others use the specification of concerns about global warming (e.g. Erdem *et al.* 2010). Kim *et al.* (2014) the perception of EV as an environmental friendly vehicle.

Since electric vehicles are still considered as modern innovative technologies, their adoption is sometimes studied as an innovation adoption behaviour. The theory of diffusion of innovations (Rogers 2003) suggest that pro-innovative attitude of an individual should have a positive effect on their perception and adoption of EVs. This suggestion was confirmed in a few choice studies, (e.g. Bočkarjova *et al.* 2013; Axsen *et al.* 2015; Sheldon *et al.* 2017), while Erdem *et al.* (2010) found its effect to be negative for hybrid electric vehicles.

Apart from pro-environmental and pro-innovativeness attitudes, other psychological factors are also expected to influence EV adoption. These include hedonic and symbolic motives for car purchase, emotions, and attitudes towards risks. Although their effect on perception of electric vehicles might be substantial, they are rarely included in choice studies. One example can be found in Helveston *et al.* (2015) who investigated the symbolic value of battery electric vehicles. They found that in the USA respondents who place high symbolic value to their car are more likely to purchase an EV, indicating that in the USA electric vehicles are associated with high social status, while the opposite was found in the case of China.

2.5.3 Car fleet characteristics

Preference for electric vehicles has also been found to be related to the characteristics of their current and expected car. The higher the number of cars that a household possesses, the higher the probability that it will choose an electric vehicle, which Kurani *et al.* (1996) formulated into a hybrid household hypothesis. It suggests that well-known shortcomings of electric vehicles, i.e. short driving range and long recharging time, can be partly overcome by relying on other vehicle when a need for longer trip or more flexibility arises. Even though many studies show this hypothesis to hold (Jensen *et al.* 2013; Qian & Soopramanien 2011; Sheldon *et al.* 2017, e.g.), there were some which found the opposite to be true (Batley *et al.* 2004; Dumortier *et al.* 2015).

In general, respondents with an intention to buy a smaller vehicle are more likely to purchase an EV (Hidrue *et al.* 2011; Hackbarth & Madlener 2013), as electric vehicles compete mainly in this segment. Moreover, having access to a charging facility at home has been found to positively influence the adoption of electric vehicles (e.g. Hidrue *et al.* 2011; Parsons *et al.* 2014).

2.5.4 Travel patterns

As for mobility patterns, their influences on EV adoption are far from conclusive. For example, while commuting distance was found negatively related with EV preference in some studies (Qian & Soopramanien 2011), daily mileage was found to positively impact EV adoption (Hackbarth & Madlener 2016). These contradictory findings regarding effects of mobility patterns, current and expected car choices, and socioeconomic characteristics on EV adoption might be caused by high correlation among these variables, as car purchase choice, for example, is usually related to socioeconomic characteristics, e.g. income, and mobility patterns are highly related to residential location of a respondent.

2.5.5 Experience with EV

Having experience with electric vehicles, e.g. through test drive or trial period, is believed to have an impact on preferences towards them. Jensen *et al.* (2013) is, however, the only study that directly examined the effect of having experience with EVs. They conducted a two-wave choice study, interviewing respondents before and after EV trial period, which lasted 3 months. They found that this experience actually confirmed respondents' worries about electric vehicles, and at the end of the trial period they favoured EVs less than before. They also concluded that respondents' attitudes and perceptions remained unaffected by this experience. Since this is currently the only study of this type, more evidence is missing, for example, whether drivers would gradually with longer time adapt their behaviour to fit the characteristics of electric vehicles and find other benefits of this technology.

2.5.6 Social influence

Decisions of an individual are often expected to be also influenced by the people in their social networks and by social norms in general. Only a few studies investigated this social influence. Whether it was measured as EV market share among the groups closest to the respondent (friends and acquaintances, or colleagues), positive or negative reviews about electric vehicles in general public (Kim *et al.* 2014; Rasouli & Timmermans 2016), or as overall EV market share (Mau *et al.* 2008), the social influence was found to have a significant although minor effect on EV preference.

2.6 Dynamic preferences

Generally discrete choice studies consider preferences to be static. If in reality preferences change, as might be the case with electric vehicles, assuming stable preferences may bring results valid for only a short period of time. Different people perceive BEVs as a new innovative technology differently, depending on a consumer's relationship to innovation. The idea is based in the theory of Diffusion of Innovation (Rogers 2003). Consumers' heterogeneity is therefore not only cross-sectional but also holds time dynamics during the whole cycle of product adoption until it wins a substantial market share. Moreover, people's preferences also evolve technological improvements that may occur faster, with current market penetration, experience with EVs, and also with social influence. There is a common implicit assumption that consumer preferences will change in favour of electric vehicles as more of them hit the road, namely 'the neighbour effect' (Sheldon *et al.* 2017).

Some reviewed studies took into consideration also the preference dynamics; however, each examined only one possible source of change in the preferences. Based on appropriate survey questions Bočkarjova *et al.* (2013) grouped respondents based on their expected time of market entry into five segments – innovators, early adopters, early majority, late majority, and traditionalists or laggards, motivated by Rogers' theory (Rogers 2003). The results indeed indicate that respondents try to satisfy different needs and form different preferences with respect to the same product. Different consumers would, therefore, also require different incentives. Mau *et al.* (2008) found evidence that consumers' preferences for hybrid electric vehicles (HEV) are dynamic, influenced by HEVs' market share. They support the idea of the neighbour effect. Finally, a minor effect of social influence factor, i.e. percentage of electric vehicles adopted by a respondent's social network, on the preference dynamics was found by Kim *et al.* (2014) and Rasouli & Timmermans (2016).

2.7 Modelling techniques

For the analysis of data from choice experiments the econometric model of choice has evolved over time. At the beginning, the majority of studies mainly estimated the most convenient conditional logit model (McFadden 1973), which is still widely utilized as the base model. However, it assumes the restrictive property of Independence of Irrelevant Alternatives (IIA), which in many cases might be unreasonable. Conditional logit will be further elaborated in Section 3.2. In an attempt to relax this assumption, some studies made use of nested logit model (Train 2003). Nested logit models cluster alternatives into several nests, allowing the alternatives within nests to be correlated. Alternatives from different nests are still considered uncorrelated.

Since both conditional logit and nested logit models estimate taste parameters as fixed constants, not accounting for the distribution of taste in the population, mainstream models later shifted towards mixed logit estimation (McFadden & Train 2000). Mixed logit model allows taste parameters to follow any prespecified distribution, as well as random terms to be correlated, hence, completely relaxing the IIA assumption. This model will be described in more detail in Section 3.3. When the mixing distribution is discrete, as discussed in Section 3.4, the conditional logit results in a latent class model (Boxall & Adamowicz 2002). This model classifies consumers into several classes based on their preferences and individual characteristics.

Recent trend in the choice modelling literature is moving toward estimating hybrid choice models (HCM) (Ben-Akiva *et al.* 2002). These models identify and incorporate latent variables, which are usually related to attitudes and/ or habits of a respondent. These latent variables are assumed to be influenced by observed variables and are measured by a number of indicators. These more advanced models generally outperform the basic conditional logit, although the issue of overfitting cannot be overlooked.

Chapter 3

Theoretical and methodological framework

3.1 Random utility model

Choice experiments are theoretically rooted in the framework of the Random Utility Model (Luce 1959; McFadden 1973), which considers the behaviour of a respondent to be utility-maximizing. Although derived from utility maximization, its application is not limited to this kind of decision making. It merely assures consistency with utility maximization, but it does not prevent the model to be consistent with other forms of behaviour.

For its derivation it is assumed that in every choice set the decision-maker chooses the alternative that brings along the highest level of utility. Since utility itself cannot be observed, it is modelled as a random variable. Thus, the utility U_{nj} of a respondent n associated with alternative j from a finite set of J alternatives is considered to be

$$U_{nj} = V_{nj} + \varepsilon_{nj},$$

where $V_{nj} = V(x_{nj}), \forall j$ is the deterministic part of the indirect utility function, often called *representative utility*. It depends on x_{nj}, a vector of observed attributes of the alternative j as faced by the decision maker n and a vector of socio-demographic characteristics of the respondent n, and on a vector of fixed unknown preference parameters β which are to be estimated statistically. V_{nj} is typically specified as linear-in-parameters, $V_{nj} = \beta^T x_{nj}$.

ε_{nj} is the stochastic part of utility - a random term, capturing the factors that affect utility but are not included in V_{nj}. Let us denote the joint density of the random vector $\varepsilon_n = (\varepsilon_{n1}, \ldots, \varepsilon_{nJ})$ as $f(\varepsilon_n)$. This density helps the researcher to make probabilistic statements about the decision maker's choice.

Thus, the probability that a respondent n would prefer option g over any alternative option h in a particular choice set can be expressed as the probability that the utility associated with alternative g is greater than that of any other alternative, which is formalized in equation (3.1).

$$P_{ng} = P(U_{ng} > U_{nh}, \forall h \neq g) = P(V_{ng} - V_{nh} > \varepsilon_{nh} - \varepsilon_{ng}, \forall h \neq g) \tag{3.1}$$

This cumulative probability can be rewritten using the density $f(\varepsilon_n)$, as follows:

$$\begin{aligned} P_{ng} &= P(V_{ng} - V_{nh} > \varepsilon_{nh} - \varepsilon_{ng}, \forall h \neq g) \\ &= \int_{\varepsilon} I(V_{ng} - V_{nh} > \varepsilon_{nh} - \varepsilon_{ng}, \forall h \neq g) f(\varepsilon_n) d\varepsilon_n, \end{aligned} \tag{3.2}$$

where $I(.)$ is the indicator function, returning 1, when the expression is true and 0 otherwise. It is a multidimensional integral over the density of the stochastic part of utility, $f(\varepsilon_n)$. In order to derive an explicit expression for this probability, the distribution of the random terms has to be specified. Different discrete choice models are obtained from different assumptions about the distribution of the random terms, i.e. from different specifications of this density.

3.2 Conditional logit model

The integral stated above results in a closed form expression only for certain specifications of $f(\varepsilon_n)$. One such specification defines a convenient, most widely used *conditional logit model*. It is obtained under the assumption that $\forall j, \varepsilon_{nj}$ is independently identically distributed (iid) with type I extreme-value (Gumbel) distribution. The density of this distribution is

$$f(\varepsilon_{nj}) = \exp(-\varepsilon_{nj}) \exp(-\exp(-\varepsilon_{nj}))$$

and its cumulative distribution function is

$$P(\varepsilon_{nj} \leq t) = F(t) = \exp(-\exp(-t)).$$

The critical part of this assumption is that the whole stochastic portion of utility is taken as independent over alternatives, as well as having the same variance for all alternatives (Hanley *et al.* 2001).

The difference between two extreme value variables is distributed logistic. That is, if ε_{ni} and ε_{nj} are iid extreme value, then $\varepsilon^*_{nij} = \varepsilon_{ni} - \varepsilon_{nj}$ is distributed logistic with cumulative distribution of:

$$P(\varepsilon^*_{nij} \leq t) = F(t) = \frac{exp(t)}{1 + \exp(t)}.$$

Then, as derived in McFadden (1973), the probability of choosing any alternative g as the best option can be expressed in a closed-form, as shown in equation (3.3).

$$P_{ng} = \frac{\exp(\alpha_n V_{ng})}{\sum_j \exp(\alpha_n V_{nj})} \tag{3.3}$$

where α_n is a *scale parameter*, inversely proportional to the standard deviation of the error distribution. This parameter cannot be identified separately from β, so it is normalized to 1 in order to set the scale of utility ε_{nj} (Hanley *et al.* 2001). The parameters are estimated using the maximum likelihood estimation, and as McFadden (1973) shows, for linear-in-parameters utility the log-likelihood function is globally concave, which simplifies the computational procedures.

3.2.1 Independence of Irrelevant Alternatives

A limiting consequence of this type of error term specification, following from the independence of the extreme value distributed error terms, is that choices among the alternative options must satisfy the Independence of Irrelevant Alternatives (IIA) property (or Luce's Choice Axiom, Luce 1959). This property states that the relative probabilities of selecting any two options are not to be affected by adding or removing other alternatives. Formally this property is expressed in equation (3.4)

$$\frac{P_{ni}}{P_{nk}} = \frac{\exp(V_{ni})/\sum_j \exp(V_{nj})}{\exp(V_{nk})/\sum_j \exp(V_{nj})} = \frac{\exp(V_{ni})}{\exp(V_{nk})} \tag{3.4}$$

As can be seen the ratio does not depend on any alternatives other than i and k. In many cases choice probabilities satisfying the IIA assumption provide an adequate representation of reality. In fact, Luce (1959) considered IIA to be property of appropriately specified choice probabilities. However, as first pointed out by Chipman (1960), in some choice situations this property turns out to be inappropriate. Mainly, when some proposed alternatives are of similar nature. Violation of IIA property would result in overestimated demand for the similar alternatives and underestimated demand for the other alternatives.

Whether IIA property holds in a specific situation can be statistically tested. Generally, two types of direct tests are suggested. First, the model can be re-estimated on a subset of the alternatives. If IIA holds, then the estimated parameters from the subset of alternatives will not be statistically different from those obtained using all the alternatives. Testing the equality of these parameters constitutes a test of IIA (Hausman & McFadden 1984). The other type is a regression-based specification test using cross-alternative variables (McFadden 1987). In this type of test variables from one alternative enter the utility of another alternative. If the ratio of probabilities for alternatives i and k depends on the presence of a third alternative j, i.e. the IIA is violated, then the attributes of alternative j will turn out to be significant. Nevertheless, as already stated by McFadden (1973) mutinomial and conditional logit models should be used only in cases where the alternatives 'can plausibly be assumed to be distinct and weighted independently in the eyes of each decision maker' [2]

3.2.2 Equal proportional substitution

Let us consider the effect of a change in an attribute of alternative j on the probability of any other alternative i. The cross-elasticity of P_{ni} with respect to a variable entering representative utility of alternative j can be derived as follows:

$$e_{iz_{nj}} = \frac{\partial P_{ni}}{z_{nj}} \frac{z_{nj}}{P_{nj}} = -\frac{\partial V_{nj}}{z_{nj}} z_{nj} P_{nj}, \tag{3.5}$$

which in case of linear specification reduces to $E_{iz_{nj}} = -\beta_z z_{nj} P_{nj}$. z_{nj} is the attribute of alternative j as presented to respondent n and β_z is its corresponding coefficient. As can be seen, i does not enter the cross-elasticity formula. A change in an attribute of alternative j changes the probabilities for all other alternatives by the same percent, i.e. the cross-elasticity is the same for all i.

This equal proportional substitution is actually a manifestation of IIA property. The ratio of probabilities for alternatives i and k stays constant with a change in an attribute of alternative j only if the two affected probabilities change by the same proportion. Using mathematical formalism, the IIA prop-

[2]Even though many authors use conditional (CL) and multinomial logit (MNL) interchangeably, there are some distinctions between the two models in the estimation process, but mainly MNL focuses on the individual as the unit of analysis and therefore includes only the individuals' characteristics in the specification x_{nj}, while CL uses the characteristics of the alternatives presented to each individual as the explanatory variables.

erty requires that

$$\frac{P_{ni}^1}{P_{nk}^1} = \frac{P_{ni}^0}{P_{nk}^0},$$

where 0 indicates the probabilities before and 1 the probabilities after the change. This equation only holds if every probability changes by the same proportion, i.e. $P_{ni}^1 = \lambda P_{ni}^0$ and $P_{nk}^1 = \lambda P_{nk}^0$.

Proportional substitution may seem reasonable in some settings, while in many situations different substitution patterns might be expected, in which cases assuming proportionality can lead to unrealistic forecasts and consequent misdesigned policy. An example can be found also within the electric car setting. Since electric cars are in general small vehicles, subsidizing them or changing one of their technological attributes can be expected to draw more from small conventional car than from large vehicles. The conditional logit in this case will overestimate the gas savings, since it overvalues the substitution away from large less fuel-efficient conventional vehicles.

3.2.3 Preference heterogeneity

The value that a single decision maker places on any attribute of an alternative in a decision-making process varies with individuals. Some differences can be linked to observed characteristics specific to a decision maker, but even when the observed characteristics of any two respondents are the same, their tastes might vary, reflecting their individual preferences and concerns.

Conditional logit model handles only systematic taste variations, which depend on observed characteristics. However, when tastes vary with unobserved variables or at least partly randomly, the model is misspecified. Moreover, conditional logit captures only the average tastes in population, assuming that respondents have the same preferences, and it does not provide information on the distribution of tastes around average. This distribution might be important when studying the preferences for a new product that might appeal to a specific group of people, not representing the average tastes.

3.2.4 Multiple observations per respondent

In many settings in stated preference experiments, multiple choice sets are presented to a single respondent. The researcher,therefore, observes a sequence of choices made by each respondent, forming a panel data structure. The assumption of independence of unobserved factors in conditional logit model, however, also applies to this sequence of choices. It is assumed that each choice is independent of the others, even though it is possible to estimate models with clustered standard errors, which attempts to correct for this shortcoming.

As such conditional logit model can capture the dynamics of repeated choices, when these are accounted for in observed factors, e.g. influence of past choices on the current ones can be specified either as the number of times the alternatives has been chosen previously, or as the attributes of this previously chosen alternative. However, it might be expected that unobserved factors affecting choice in one period would persist, resulting in dependence among the choices over time. Conditional logit cannot handle correlations of unobserved factors and hence other error term specification could be used instead.

3.3 Mixed logit model

All of the limitations of conditional logit listed above can be overcome with the use of *mixed logit model*. It relaxes the IIA assumption, does not require a specific substitution pattern, and it allows random taste variation, and correlation in unobserved factors. McFadden & Train (2000) show high flexibility of this model and its ability to approximate any random utility model.

In general, a mixed logit model is any model whose choice probabilities can be expressed as the integrals of logit probabilities over a density of parameters $f(\beta)$. The formula is stated in equation (3.6). It is actually a mixture of the logit function evaluated at different parameters β with $f(\beta)$ as a mixing distribution. Mixed logit model does not place any restrictions on the assumed distribution of $f(\beta)$, although most common is continuous specification — normal, lognormal, uniform, gamma, etc.

$$P_{ng} = \int \frac{\exp(V_{ng}(\beta))}{\sum_j \exp(V_{nj}(\beta))} f(\beta) d\beta, \tag{3.6}$$

where $V_{ng}(\beta)$ represents the observed portion of utility evaluated at parameters β. Most often utility is taken as linear in parameters, $V_{ng}(\beta) = \beta^T x_{ng}$. Then, the mixed logit probability takes the form of:

$$P_{ng} = \int \frac{\exp(\beta^T x_{ng})}{\sum_j \exp(\beta^T x_{nj})} f(\beta) d\beta. \tag{3.7}$$

The mixed logit reduces to standard conditional logit, when the mixing distribution $f(\beta)$ takes the form of: $f(\beta) = 1$ when $\beta = B$ and $f(\beta) = 0$ when $\beta \neq B$, for fixed parameters B. The parameters are estimated using the maximum simulated likelihood estimation.

3.3.1 Random-coefficient logit

Within this formulation there are two sets of parameters to be estimated — the parameters β which enter the logit probabilities with density $f(\beta)$, and the parameters that describe this density, which can be denoted as θ. Usually, one is interested mainly in these density parameters. Then, the mixed logit choice probabilities, expressed in equation (3.8), are functions of θ, and the parameters β are integrated out.

$$P_{ng} = \int \frac{\exp(\beta^T x_{ng})}{\sum_j \exp(\beta^T x_{nj})} f(\beta|\theta) d\beta. \tag{3.8}$$

With this interpretation of mixed logit model, *random taste coefficients* are estimated, and possibly also the correlation between them. Allowing the coefficients to vary within prespecified distribution implies the fact that different decision makers may have different preferences.

3.3.2 Error-component logit

Mixed logit model can be also used without this interpretation of random coefficients, representing simply *error components* that enable correlations among the utilities associated with different alternatives. Following Brownstone & Train (1998) the linear-in-parameters utility function can then be specified as:

$$U_{nj} = \beta^T x_{nj} + \mu_n^T z_{nj} + \varepsilon_{nj},$$

where $\beta^T x_{nj}$ is the deterministic part of utility as described above, z_{nj} is a vector of observable variables relating to alternative j, μ_n is a random vector with zero mean, and ε_{nj} is again iid extreme value. Thus, the stochastic portion of utility is given by $\eta_{nj} = \mu_n^T z_{nj} + \varepsilon_{nj}$.

The correlation between alternatives in unobserved attributes is achieved by non-zero random terms in $\mu_n^T z_{nj}$, which can be considered as error components. Complexity of the correlation structure depends on the specification of z_{nj} [3],

[3]When all terms in z_{nj} are identically zero, suggesting no unobserved correlation over alternatives, the conditional logit is obtained

as $cov(\eta_{ni}, \eta_{nk}) = E(\mu_n^T z_{ni} + \varepsilon_{ni})(\mu_n^T z_{nk} + \varepsilon_{nk}) = z_{ni}^T W z_{nk}$, where W is the covariance of μ_n. Error-component and random-coefficient specification are formally equivalent but allow for different interpretation and use.

3.3.3 Panel data

In contrast with the standard conditional logit, the mixed logit specification can be easily generalized to allow for repeated choices made by the same respondent, which is often the case in discrete choice studies. The simplest such specification allows the coefficients entering utility function to vary between different respondents but keeps them constant over choice situations of a single person (Hess *et al.* 2011).

Using the random-coefficient linear-in-parameters specification, the utility from alternative j in choice task t out of T made by a respondent n changes to $U_{njt} = \beta_n x_{njt} + \varepsilon_{njt}$, where ε_{njt} is iid extreme value over alternatives, respondents, and time. Conditional on β, the probability that a respondent makes a specific sequence of choices is a product of logit probabilities

$$L_{ng}(\beta) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta^T x_{ngt})}{\sum_j \exp(\beta^T x_{njt})} \right]^{y_{ngt}},$$

where $y_{ngt} = 1$ if the individual chooses alternative j in choice task t and 0 otherwise. The unconditional probability is the integral of this product over all values of β

$$P_{ng} = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta^T x_{ngt})}{\sum_j \exp(\beta^T x_{njt})} \right]^{y_{ngt}} f(\beta|\theta) d\beta.$$

3.4 Latent class model

The mixing distribution $f(\beta)$ in equation (3.7) can also be of discrete nature. Letting β take Q possible values $B_1, \dots, B_Q$, with probability s_q that $\beta = B_q$, gives rise to the *latent class model*. With this specification it is assumed that there exist Q distinct classes in the population, where the individuals within each segment are characterized by homogeneous preferences, while the utility functions can differ between groups. The classes are said to be 'latent' because respondents are not actually observed to belong to any specific preference group. The share of class q in the population is given by s_q, which is to be estimated within the model along with preference parameters B_q for each class q.

Hence, a latent class model is given by two separate probabilistic models, which are estimated simultaneously. First model is a choice model which explains choices among alternatives presented to a respondent in different choice tasks, conditional on their membership to a specific segment. Second is a class membership model which groups the decision-makers into the Q classes, based, for example, on their socio-demographic characteristics, their attitudes or habits.

Taking into account the panel data structure from multiple choice situations given to a single respondent and assuming linear-in-parameters utility function, the utility that an individual n selects alternative j in choice task t is formulated as

$$U_{njt} = \beta_q^T x_{njt} + \varepsilon_{njt},$$

where β_q is a fixed class-specific vector of parameters, and ε_{njt} is again iid extreme value over alternatives, respondents, and time. Conditional on a specific class membership, the probability that a decision-maker n belonging to class q makes the observed sequence of choices is given by

$$L_{ng}(\beta_q) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_q^T x_{ngt})}{\sum_j \exp(\beta_q^T x_{njt})} \right]^{y_{ngt}},$$

where $y_{ngt} = 1$ if the individual chooses alternative j in choice task t and 0 otherwise. The probability that decision-maker n actually belongs to class q within standard conditional logit specification is expressed as

$$H_{nq} = \frac{\exp(\gamma_q^T z_n)}{\sum_q \exp(\gamma_q^T z_n)}, \tag{3.9}$$

where z_n is a vector of observed characteristics of a decision-maker n, γ_q is a class-specific vector of parameters, and $\gamma_Q = 0$ to allow for interpretability. The unconditional probability that a randomly chosen decision-maker n chooses a given observed sequence of alternatives is then obtained by multiplying the conditional probability by the probability of belonging to a specific class q

$$P_{ng}(\beta_q) = \sum_q H_{nq} L_{ng} = \sum_q H_{nq} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_q^T x_{ngt})}{\sum_j \exp(\beta_q^T x_{njt})} \right]^{y_{ngt}}. \tag{3.10}$$

This probability enters the likelihood function, which is then maximized directly using standard maximization methods, or indirectly using Expectation-Maximization (EM) algorithm (Train 2008).

The number of consumer segments Q is also unknown and needs to be specified prior to estimating the latent class model. There is, however, no one rigorous way to select the 'right' Q, but rather several decision criteria have been recommended to guide this selection, such as the Akaike Information Criterion (AIC), Consistent AIC (CAIC), or the Bayesian Information Criterion (BIC) (Louviere *et al.* 2000). The common procedure involves estimating the final model specification with varying number of classes. The model, which minimizes the different selection criteria, does not yield a large number of insignificant parameters, and/or does not produce very infrequent counterintuitive segment, is the one that should be preferred. But as Louviere *et al.* (2000) state the final decision should be guided by analyst's judgement to enable meaningful behavioural interpretability.

By assuming that the population is composed of a finite number of different segments, latent class model captures preference heterogeneity and so improves this shortcoming of conditional logit model. Swait (2007) also shows that latent class model is not constrained by the IIA property, and can handle correlations of repeated choices of a single respondent. Moreover, some studies have also found evidence suggesting latent class model might be advantageous over other mixed logit specifications (Greene & Hensher 2003; Hess *et al.* 2011; Sagebiel 2011).

These advantages mainly result from semiparametric specification of latent class model, which relaxes possibly strong or unjustified distributional assumptions about preference heterogeneity imposed within mixed logit models. Other advantage of latent class model comes at the interpretation stage, as it provides clear connection to socio-demographic indicators. Nevertheless, no unambiguous preference of latent class over mixed logit models was found, they both have own merits, which can be properly exploited given circumstances (Greene & Hensher 2003).

3.4.1 Individual-level parameters

The class probabilities specified in Equation 3.9 represent the prior class membership probabilities. After estimating the parameters it is also possible to gain the posterior class membership probabilities. With linear-in-utility specification these are given in the following formula:

$$G_{ng} = \frac{H_{nq} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_q^T x_{ngt})}{\sum_j \exp(\beta_q^T x_{njt})} \right]^{y_{ngt}}}{\sum_q H_{nq} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_q^T x_{ngt})}{\sum_j \exp(\beta_q^T x_{njt})} \right]^{y_{ngt}}}. \tag{3.11}$$

With the use of these posterior probabilities estimates of individual-level coefficients can be obtained. The expected value of β conditional on a certain response sequence made by an individual n, y_n, and a set of alternatives characteristics, x_n is given by

$$E[\beta | y_n, x_n] = \sum_q \beta_q G_{nq}.$$

Hence, the estimates of β_n can be gained by plugging in the estimates of β_q and G_{nq} into the formula, and then the distribution of the individual-level coefficients for specific attributes can be obtained.

3.5 Willingness-to-pay measure

Willingness-to-pay welfare measure is defined as the maximum amount of income a person would pay in exchange for an improvement in circumstances, or the maximum amount a person will pay to avoid a decline in circumstance (Haab & McConnell 2002, pg. 6). Once using the methods described in previous sections the parameter estimates have been obtained, WTP estimates can be derived using the formula given in the following equation.

$$WTP = b_C^{-1} \ln \left\{ \frac{\sum_i \exp(V_i^1)}{\sum_i \exp(V_i^0)} \right\}, \tag{3.12}$$

where b_C is the coefficient of the cost attribute, usually of the purchase price, V^0 represents the utility associated with the initial state and V^1 gives the utility of the alternative state (Hanley *et al.* 2001).

It is possible to show that for the linear in parameters utility specification, the formula above is simplified to the ratio of coefficients

$$WTP = -\frac{b_X}{b_C}, \tag{3.13}$$

where b_X is the coefficient on any of the other attributes, which improvements are to be valued, holding everything else constant.

When latent class modelling framework is utilized, the final WTP values are obtained as a weighted average of WTP values from individual classes, with weights being the class probabilities as stated in Equation 3.9:

$$WTP = \sum_{q} H_{nq} \left(-\frac{b_X}{b_C} \right). \tag{3.14}$$

Even though obtaining WTP values with linear-in-parameters utility is relatively simple, once the parameter estimates are known, specifying standard errors for these ratios is more complex. As it is a non-linear function of the parameter estimates, the asymptotic distribution of the maximum likelihood estimator of the welfare measure is not known and has to be obtained using simulations (Hanley *et al.* 2001).

Chapter 4

Experimental design and data

4.1 Method

4.1.1 Method of valuation

In order to understand choice of consumers among conventional car (fuelled by petrol, diesel, or oil derivatives, e.g. LPG) and three types of electricity driven vehicles, specifically battery electric car, hybrid and plug-in hybrid vehicle, the discrete choice experiment stated preference method of valuation was used. (Discrete) choice experiments (sometimes also known as conjoint analysis) are a family of survey-based methods for modelling preferences for goods, where the goods are described by their attributes and the associated levels that these take. Respondents are shown different alternatives of a good, which differ in their attributes and levels, and are asked to rank the alternatives, to rate them or to choose their most preferred option. By the inclusion of price/ cost as one of the attributes, willingness-to-pay for specific attributes of vehicles can be estimated from people's rankings or choices (Hanley *et al.* 2001). The conceptual microeconomic framework for choice experiments was derived from characteristics theory of value of Lancaster (1966), which assumes that utility for a specific good can be decomposed into utilities for characteristics of the composing elements, and choice responses are assumed to be rooted in an underlying random utility model, which was described in more detail in Section 3.1.

For the choice experiment designed and used in Ščasný *et al.* (2015), which data will be analysed in this work, they specifically used sequences of multinomial choice questions. In the experiment cars differentiated in the levels of two or more attributes. Based on the literature review and pre-survey they identified six attributes, one of which was the purchase price of a vehicle. The remaining attributes selected composed of: operational costs, driving range, refuelling/ recharging time, availability of fast-mode recharging infrastructure, and other benefits, consisting of free parking and free public transport. Attributes and their levels used in the choice experiments can be found in Table 4.1. Respondents were asked to choose their most preferred option among conventional, hybrid electric, plug-in hybrid electric and battery electric vehicles described by varying levels of the attributes stated above.

4.1.2 Experimental design

Regarding the experimental design of the survey, it consisted of 40 choice tasks, with 4 alternatives each. Status-quo option was not included, although conventional vehicle alternative was designed to represent the closest choice to the one respondent stated they intend to buy. There were 5 questionnaire versions with 8 choice tasks per respondent. In order to mitigate anchoring or framing effects the order of choice tasks in each version and the order of alternatives in each choice task was randomized, different for every respondent. The alternatives were labelled, depicting different fuel technology—conventional vehicle, hybrid vehicle, plug-in hybrid electric vehicle, and battery electric car). After gaining information about the car that respondents intend to buy, whether new or used, and the corresponding price range, as well as information about the expected use patterns of a respondent, i.e. expected annual mileage, the attribute levels in the choice tasks were made individual specific. Rather than using averages, alternative- and respondent-specific values were used to define their levels in the choice experiment design. This pivotal design helped to add more relevance and comprehensibility to the attributes being assessed (Rose *et al.* 2008).

The experimental design was optimized for D-efficiency of the multinomial logit model using Bayesion priors (Ščasný *et al.* 2015). D-efficiency is one of the criteria used to assess the statistical efficiency of a study, based on the minimization of the variance-covariance matrix of parameter estimates (Ferrini & Scarpa 2007). The Bayesian efficiency of the study design was approximated by a quasi Monte Carlo method (Bliemer *et al.* 2008). The median of 1000 Sobol draws was taken as an indicator of the central tendency. All priors, except for the prior estimates of alternative specific constants (ASCs), were assumed to be normally distributed. Due to possible high heterogeneity of respondents' preferences towards different propulsion technologies, priors of ASCs were as-

Table 4.1: Vehicle attributes and levels used in the DCE

Variable	Units	Fuel types	No. of levels (%)	Levels (%)
Purchase price (PP)	złoty	CV	1	As stated by the respondent
		HV, PHEV	7	0%, 90%, 100%, 110%, 120%, 130%, 140% of price of conventional vehicle
		BEV	7	80%, 90%, 100%, 110%, 125%, 133%, 145% of price of conventional vehicle
Operational costs (OC)	złoty/ 100km (złoty/ month)	CV	4	FC = 25, 30, 40, 50 OC = 4000 * annual mileage in 100km as stated by the respondent
		HEV	2	FC = 90%, 100% of FC of conventional vehicle OC = 5000 * annual mileage in 100km as stated by the respondent
		PHEV	2	FC = 70%, 90%, 100% of FC of conventional vehicle OC = 5000 * annual mileage in 100km as stated by the respondent
		BEV	3	FC = 25%, 40%, 75% of FC of conventional vehicle OC = 2000 * annual mileage in 100km as stated by the respondent
Driving range (DR)	max km	CV, HEV, PHEV	3	500km, 700km, 900km
		BEV	4	150km, 250km, 350km, 500km
Refuelling/ recharging time (RT)	hrs and mins	CV, HEV	1	2min
		PHEV	3	30min, 1hr, 3hrs
		BEV	3	2hrs, 4hrs, 7hrs
Availability of fast-mode recharging	% of fuel stations and public places	PHEV, BEV	3	low = 20% of fuel stations and at few public places; medium = 60% of fuel stations and at half of public places (FM2); high = 90% of fuel stations and at almost all public places (FM3)
Other benefits		HEV, PHEV, BEV	4	None, free parking (FP), free public transport (FT) both free parking and free public transport

Notes: FC - fixed costs; OC - operational costs; CV - conventional vehicle; HEV - hybrid electric vehicle; PHEV - plug-in hybrid electric vehicle; BEV - battery electric vehicle sumed to follow a uniform distribution. The means of the Bayesian priors were estimated using a multinomial logit model (MNL) on data from the pilot survey, and standard deviations were set equal to 0.25 of the mean value of each parameter (Ščasný *et al.* 2015).

Hence, the utility that a respondent n associates with alternative j from a finite set of alternatives — CV, HEV, PHEV, BEV — would specifically for this design be assumed in the following form:

$$U_{nj} = \beta_0 + \beta_1 PP_{nj} + \beta_2 OC_{nj} + \beta_3 DR_{nj} + \beta 4 RT_{nj} + \beta_5 FM2_{nj} + \beta 6 FM3_{nj} + \beta 7_F T_{nj} + \beta_8 FP_{nj} + \epsilon_{nj}, \quad (4.1)$$

where the independent variables are represented by the attributes and their levels, as described in Table 4.1. The associated willingness-to-pay estimates, theoretically described in Section 3.5, would then for all other attributes be calculated using the purchase price as follows:

$$WTP = -\frac{b_i}{b_1}, \quad (4.2)$$

where $i = 2, 3, \ldots, 8$.

4.1.3 The questionnaire

The final version of the questionnaire used in the main wave of data collection, including hypothetical scenarios of choice tasks, was fine-tuned during pre-survey (11 semi-structured interviews) and pilot testing (407 interviews conducted in this phase). The structure of the questionnaire follows a common ordering of questions, although a sociodemographic section was placed in the beginning in order to control for quota attainment, which is recommended for computer-assisted web interviews (CAWI) (Ščasný *et al.* 2015).

4.2 Data

For our purposes data from a questionnaire survey of the adult population of Poland conducted in 2014 by Millward Brown [4] will be analysed. The sur-

[4]Millward Brown's online panel IBIS has been in operation since 2006. It complies with the ICC/ESOMAR Code on Market and Social Research and the ISO 20252 standard. The panel holds the certificate of the ISO 26362 for access panels. Millward Brown respects and abides by the law, including the Civil Code, the Law on Personal Data Protection, the Law

vey took the form of computer-assisted web interview (CAWI). In total 2613 respondents completed the interview, including 407 from the pilot testing. Resulting completion rates were 38.6% and 38.8% for the main and pilot wave, respectively. The data consists of two independent samples:

- Sample A contains Polish respondents who intend to buy a passenger vehicle with quotas set for age, gender, and region of residence. At the very beginning of the questionnaire respondents, not knowing the objective of the study, were asked to choose from a list of items something they intend to buy within the next three years. This screening question ensured that only respondents with real intention to buy a car in the specified period were included. Next a question whether the intended car is going to be new or used was placed. The share of people to buy a new car or those who were still undecided, and those with an intention to buy a second-hand vehicle was arbitrarily set to be even in order to gain sufficient number of observations for new car buyers, as it is more common to buy an used car rather than brand new one in Poland.

- Sample B is a representative sample of the general Polish population with sampling quotas for age, gender, region, size of the place of residence, and education. This sample was selected independently from the sample A and it also included respondents with the intention to buy a new or a used vehicle, but in this case the proportion of each group was representative of the general tendency in Polish population. In Sample B, moreover, only respondents who stated clear intention to buy a car in the future, regardless of the time horizon, were asked to complete the discrete choice experiment — 52.5% of those who starting filling out the questionnaire. Otherwise their answers might be too hypothetical.

The collected data were cleaned; incomplete cases were excluded and all logical combinations were tested. Taking into account only respondents who completed the discrete choice experiment and where there were no errors (most likely caused by returning to previous questions and changing the answers) identified, the sample size reduces to 2,255 completed interviews—1,748 in Sample A and 507 in Sample B. Moreover, the median time to complete the

on Unfair Competition, and the Law on Copyright and Related Rights. At the moment of data collection the panel consisted of 83,000 active respondents, where an active panellist is a person who has participated in at least one study during the preceding year. The incentive system used in the panel is a loyalty program.

questionnaire was identified. The completion time depended on whether the respondent possessed a car, whether they intended to buy a vehicle, as well as whether they were included in Sample A or Sample B. Those who completed the survey in less than 48% of the median time were identified as speeders, as recommended by SSI (Survey Sampling International, 2013). Finally, 84 speeders out of 1,748 respondents or 4.8% were found in Sample A and 30 out of 507 or 5.9% in Sample B. In total 114 out of 2,255 or 5.1% of respondents were identified as speeders. The final sample sizes for both samples in each wave–pilot and main–can be found in Table 4.2.

Table 4.2: Number of respondents by sample and wave

	Sample A	Sample B	Total
Pilot – excl. speeders	334	25	359
Pilot – speeders	21	3	24
Main wave – excl. speeders	1,330	452	1,782
Main wave – speeders	63	27	90
No. obs. – incl. speeders	1,748	507	2,255

Excluding speeders, error and illogical observations, as described above, in some way changed the composition of our samples with respect to quotas specified in advance. Hence, Table 4.3 and Table 4.4 show comparison of key characteristics of Sample A and Sample B with the ones of the target population, based on which quotas were selected. The share of females and males closely follow the gender representation among the panel composed of car drivers in Poland, however, there might be in general more female panellists, so in reality the share of female car drivers might be lower. On the contrary, in Sample B female respondents might be slightly underrepresented.

In both samples younger adult respondents below the age of 30 years are evidently overrepresented at the expense of those above 50 years of age, which considered to the general trend in Internet based surveys. The spatial distribution of respondents in Poland in both sample also seem to meet the set-up quotas, although in Sample B substantially more respondents live in highly populated municipalities than would be expected. Regarding educational level, the least educated respondents seem to be underrepresented at the expense of those who finished secondary but not higher education.

Moreover, in Sample A, in a sample in which respondents demonstrated their intention to buy a passenger vehicle, 87.9% of respondents intended to do so within 3 years after the survey, 8.7% between 4 and 5 years, and only the remaining 3.43% of respondents planed car purchase later or were still undecided. Also in Sample B, representing the general Polish population, almost all respondents intended to buy a vehicle sometime in the future, although in this group only 72.24% intended this purchase within 3 years after the survey, 19.5% between 4 and 6 years, and 8.3% of respondent in Sample B intended to buy a car later or were undecided.

The distribution of intended car type, whether new or used one, also differed between the two samples. As was mentioned above, in Sample A the proportion of those intending to buy a new car, and those intending to buy a used car or were still undecided was arbitrarily set to be even. Excluding the problematic observation, however, resulted in the fact that 51% of respondents in Sample A stated their intention to buy a new car, while 49% were undecided or intending to buy a used car. In Sample B as much as 66.3% of respondents stated their intention to buy a used car, while only 33.7% of Sample B were still undecided or leaning towards the possibility of buying a brand new one.

Table 4.3: Characteristics of the Sample A vs. target population

Variable	Value	Sample A (%)	Target Population (%)
Gender	Male	46.4	46
Age	18-29 years	30.0	26
	30-49 years	47.9	46
	50 years or above	22.1	28
Region	Centralny	20.2	21
	Południowy	22.8	22
	Wschodni	18.3	17
	Północno-zachodni	14.4	15
	Południowo-zachodni	11.1	10
	Północny	13.3	16

Source: Target Group Index (Structure of car drivers in Poland)

Table 4.4: Characteristics of the Sample B vs. Polish population

Variable	Value	Sample B (%)	Population (%)
Gender	Male	52.6	50
Age	18-29 years	29.3	24
	30-49 years	41.2	40
	50 years or above	29.5	36
Size of municipality	Up to 20,000 inhabitants	46.1	52
	20,000-200,000 inhabitants	28.7	27
	200,000 or more inhabitant	25.2	21
Region	Centralny	17.9	21
	Południowy	21.5	21
	Wschodni	16.9	17
	Północno-zachodni	18.3	16
	Południowo-zachodni	10.0	10
	Północny	15.4	15
Education	Primary and vocational	41.7	46
	Secondary	39.4	35
	Higher	18.9	19

Source: Central Statistical Office of Poland.

Chapter 5

Empirical results

The data gathered from the choice experiment reveals that respondents in both samples made very similar choices. Majority of people favoured conventional vehicles, followed by battery electric one. Both hybrid electric vehicles seem to be the least preferred among the respondents. This distribution of choices between the presented alternatives can be found in Table 5.1.

Table 5.1: Distribution of choices among alternatives

Alternative	Sample A (%)	Sample B (%)
Conventional vehicle	36.1	35.8
Hybrid electric vehicle	14.6	14.9
Plug-in hybrid electric vehicle	23.2	22.9
Battery electric vehicle	26.1	26.3
Total	100	100

The empirical analysis of the acquired data was based on conditional logit (CL) model. As stated in Section 3.2 this model assumes the restrictive independence of irrelevant alternatives (IIA) property. Conducting specification tests as suggested by Hausman & McFadden (1984), evidence against this strong IIA assumption was found in both samples. Running nested logit models on the data also rejected the hypothesis that IIA assumption would hold.

In order to relax this restrictive IIA assumption, mixed logit specification model, as described in Section 3.3, was also performed on data from both samples. Assuming normal distribution of all attributes from Table 4.1 except for the purchase price, both mixed logit (MXL) model specifications —with correlated and uncorrelated random coefficients —result in very large estimated standard deviations relative to the estimated means, suggesting high heterogeneity of preferences towards electricity-driven vehicles and their attributes among the respondents in both samples. The actual parameter estimates of the basic conditional logit and both mixed logit model specifications can be found in Appendix A.

In order to better account for this preference heterogeneity and to find explanation of its observed part, latent class (LC) modelling approach was applied on the data. As was described in Section 3.4, using this framework it is possible to examine whether distinct segments with significantly varying preferences exist in the population and also how these groups differ regarding their compositions. The most appropriate number of classes was selected by first estimating the latent class models with different number of classes (2-12), and then making selection based on the Akaike's information criterion (AIC), consistent AIC (CAIC) and Schwarz's Bayesian information criterion (BIC). The most preferred model is found, when these information criteria are minimized. [5]

The information criteria values for the latent class models with varying number of classes as well as those associated with conditional logit and both mixed logit models can be found in Table 5.2 for Sample A and in Table 5.3 for Sample B. LC model with only two latent classes is already found to outperform the conditional logit model, which is actually LC model with only one latent class. Moreover, the information criteria suggest that the mixed logit with uncorrelated parameters performs worse than latent class model with three and more latent classes, while the mixed logit with correlated parameters is worse than LC model with 7 and more latent classes according to AIC, and 6 and more latent classes according to BIC, for Sample A. In Sample B already LC model with 4 classes performs better than mixed logit with correlated parameters according to BIC, while AIC would suggest using LC model with 8 and more latent classes.

Overall, from all of the considered models AIC information criterion points towards estimating LC model with as many as 12 latent classes in Sample A, and with 9 latent classes in Sample B, while BIC measure would suggest estimating LC model with 9 latent classes in Sample A, and with 6 latent classes in Sample B. However, models with higher numbers of latent classes

[5] With $\ln L$ representing the maximized log-likelihood of the model, k being the number of parameters, and N the sample size, the information criteria are defined as $\text{AIC} = -2\ln L + 2k$, (Akaike 1974); $\text{CAIC} = -2\ln L + k\ln(N+1)$, (Bozdogan 1987); $\text{BIC} = -2\ln L + k\ln N$, (Schwarz *et al.* 1978).

Table 5.2: Class selection criteria for Sample A data

	MXL uncorr	MXL corr	LC (No. of classes)											
			1 (CL)	2	3	4	5	6	7	8	9	10	11	12
LL	-14,213.1	-13,302.5	-17,185.4	-15,082.4	-14,012.6	-13,744.3	-13,497.9	-13,325.7	-13,183.9	-13,114.7	-13,057.1	-13,021.7	-12,964.8	-12,942.5
AIC	28,468.3	26,737.0	34,392.8	30,210.7	28,095.2	27,582.6	27,113.9	26,793.4	26,533.9	26,419.5	26,328.3	26,281.3	26,191.7	26,171.1
CAIC				30,358.3	28,319.8	27,884.2	27,492.5	27,249.0	27,066.5	27,029.1	27,014.9	27,044.9	27,032.3	27,088.7
BIC	28,654.8	27,323.2	34,490.5	30,335.3	28,284.8	27,837.3	27,433.5	27,178.0	26,983.5	26,934.1	26,907.9	26,925.9	26,901.3	26,945.7
No. of parameters	21	66	11	23	35	47	59	71	83	95	107	119	131	143

Table 5.3: Class selection criteria for Sample B data

	MXL uncorr	MXL corr	LC (No. of classes)											
			1 (CL)	2	3	4	5	6	7	8	9	10	11	12
LL	-4,045.0	-3,742.7	-4,949.4	-4,306.2	-4,013.3	-3,904.5	-3,809.6	-3,767.4	-3,733.2	-3,696.3	-3,657.9	-3,647.4	-3,677.7	-3,594.8
AIC	8,131.9	7,617.3	9,920.7	8,658.4	8,096.6	7,903.1	7,737.2	7,676.8	7,632.5	7,582.5	7,529.8	7,532.8	7,617.4	7,475.5
CAIC				8,777.3	8,277.6	8,146.0	8,042.2	8,043.8	8,061.6	8,073.7	8,082.9	8,148.0	8,294.6	8,214.8
BIC	8,292.2	8,121.3	10,004.7	8,754.3	8,242.6	8,099.0	7,983.2	7,972.8	7,978.6	7,978.7	7,975.9	8,029.0	8,163.6	8,071.8
No. of parameters	21	66	11	23	35	47	59	71	83	95	107	119	131	143

resulted in rather infrequent classes with probabilities of belonging to them of less than 5%. Moreover, as proposed by Louviere *et al.* (2000) the number of latent classes should be chosen such that the final model enables meaningful behavioral interpretability, but increasing number of latent classes makes the interpretation harder.

The models with 2 latent classes using all data in both samples divide the respondents into those preferring electricity-driven vehicles (67.9% in Sample A and 64.7% in Sample B) and those with strong preferences for conventional vehicles (32.1% in Sample A and 35.3% in Sample B). All the models with 2 latent classes can be found in Appendix B. This rather high share of those preferring electric vehicles is further explained in models with three latent classes, where the distribution of preferences among the respondents is subtler and almost even —30.5% in Sample A and 31.2% in Sample B preferring pure battery electric vehicles; 40.5% in Sample A and 36.4% in Sample B with significant preferences towards hybrid vehicles, both plug-in hybrids and pure hybrids; and 28.9% in Sample A and 32.4% in Sample B with strong preferences for conventional vehicles.

Models with 4 latent classes made even subtler division, but only models with 5 latent classes provided clear division into those with strong opposition to electric vehicles, hence strong preference for conventional ones (22.3% in Sample A and 22.9% in Sample B), those with weaker preferences for conventional vehicles (28.9% in Sample A and 21.4% in Sample B), those significantly preferring pure hybrid vehicles (9.5% in Sample A and 21.1% in Sample B), those with strong preferences for plug-in hybrid vehicles (14.7% in Sample A and 12.3% in Sample B), and those with significant preferences for pure battery electric vehicles (24.7% in Sample A and 22.2% in Sample B). Starting with 6 latent classes, models provided only even subtler division of respondents into preference classes stated above, so in order to ensure meaningful interpretability, models with 3 and 5 latent classes were chosen for further analysis.

Attributes used in the discrete choice experiment, which were described in Table 4.1, enter the utility part of the LC models as variables, defined as stated in Table 5.4. Different specifications of these variables were tested, e.g. logarithmic, square root, and stepwise, but they did not provide statistically significant improvements. Hence, purchase price, operational costs, driving range and refuelling/recharging time were used in their levels, fast-mode recharging (the excluded category being low availability, i.e. at 20% of fuel stations and at few public places), free parking and free public transport incentives, and fuel type (the excluded category being conventional vehicle) as dummies.

Table 5.4: Definition of variables used in the utility part of LC models

Variable	Definition
Purchase price	Purchase price in 10,000zł
Operational costs	Operational costs in 100zł per 100km
Driving range	Maximum driving range in 100km
Refuelling/recharging time	Refuelling/recharging time in hours
Fast-mode recharging 2	1 if fast-mode recharging is available at 60% of fuel stations and at half of public places; 0 otherwise
Fast-mode recharging 3	1 if fast-mode recharging is available at 90% of fuel stations and at almost all public places; 0 otherwise
Free parking	1 if free parking incentive is granted; 0 otherwise
Free public transport	1 if free public transport incentive for the respondent and their family members is granted; 0 otherwise
HEV	1 if fuel type is hybrid electric; 0 otherwise
PHEV	1 if fuel type is plug-in hyrbid electric; 0 otherwise
BEV	1 if fuel type is battery electric; 0 otherwise

The definitions of membership variables used in the class assignment functions of the final models along with their descriptive statistics in both samples are shown in Table 5.5. Sociodemographic variables such as gender, age, education level, or marital status of a respondent were generally found insignificant, so they were not included in the final models. From the socioeconomic variables only household income was included. The included class assignment variables consist mainly of respondent's living characteristics, their attitudes and norms, and their expected car fuel type. These membership variables are then used to make distinctions between the classes found. For better comparison between the results, in all models the same membership variables were included.

In what follows, the results from models with 3 and 5 latent classes using data on respondents with an intention to buy a vehicle from Samples A and B will be presented. These can be found in Table 5.6, Table 5.7, Table 5.8 and Table 5.9, respectively. In the following tables along with parameters estimates for simple conditional logit and every class of a LC model, results are also presented as willingness to pay estimates for every model, as well as a probability weighted average for latent classes.

Presentation of results using WTP estimates provides more convenient interpretation, but is otherwise equivalent to using parameters estimates only. As was described in Section 3.5, the WTP estimates are obtained by dividing attributes parameters by the purchase price parameter. For the interpretation it is important to keep in mind that purchase price was expressed in 10,000zł,

Table 5.5: Definition and descriptive statistics for membership variables used in LC models

Variable	Description	Sample A		Sample B	
		% in sample	Mean (SD)	% in sample	Mean (SD)
City center	1 if living in the centre of a city or town; 0 otherwise	38.3		40.3	
Suburbs	1 if living in the suburbs of a city or town; 0 otherwise	32.1		28.9	
Family house	1 if living in a family house or family villa; 0 otherwise	52.5		46.3	
Garage at home	1 if possible to park a car in a garage at home; 0 otherwise	52.3		45.3	
Missing income	1 if income not reported by the respondent; 0 otherwise	7.8		5.9	
Household income	Monthly net household income (in zł)		4,257.9 (3,332.0)		3,578.3 (2,579.9)
Diesel	1 if expecting next purchase fuel type is diesel; 0 otherwise	37.1		36.3	
AFV	1 if expecting next purchase fuel type is CNG/LPG, electricity or biofuels; 0 otherwise	40.6		42.4	
Personal norms	Sum of two 7-level Likert scales capturing concerns about the environment (min = 2, max = 14)		6.5 (4.1)		8.0 (3.3)
Technophilia	Factor of two 7-level Likert scales capturing enthusiasm for new technologies (min = 2, max = 14)		8.0 (4.6)		9.7 (3.4)
Multicar	1 if the household owns 2 or more cars; 0 otherwise	41.2		29.4	
Social group	1 if > 5 on a 7-level Likert scale about probability of respondents' closest ones to buy an EV;0 otherwise	8.7		10.1	

Notes: Either % or mean with standard deviation (SD) is presented, depending on whether the variable is a dummy or not.

so the WTP estimates should be multiplied by 10,000 to get equivalent in zł. Moreover, operational costs were specified in 100zł per 100km and driving range in 100km, so estimates for operational costs should be multiplied by 100 instead to obtain WTP estimate for 1zł decrease in operational costs per 100km, and estimates for driving range should be multiplied by 100 to get WTP estimate for one additional km in driving range.

In Sample A, LC model with 3 latent classes suggests that compared to those with strong opposition to any electric vehicles, those who prefer hybrid vehicles are richer, already more likely to consider buying an AFV, and their closest ones are also more likely to buy an EV. Those preferring battery electric car are also found to be already more likely to consider buying an AFV, are closely surrounded by like-minded people, and moreover, significantly more likely to live in a family house. Similar results are found when considering the model with 5 latent classes. Those with weak and strong preference for conventional vehicles are less likely to have those who consider buying an EV in their closest networks.

In Sample B those preferring hybrid vehicles are more likely to be living in a city center or in the suburbs, as model with 3 latent classes would suggest. This group is also found to be prone to adopting new technology products. Those with strong preference for battery electric vehicles are then more probable to

Table 5.6: Model with 3 latent classes using all data from Sample A (Std. Errors in paretheses)

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class-specific parameters									
Purchase price	-0.366***	-0.604***	-0.287***	-0.455***					
(in 10,000zł)	(0.03)	(0.03)	(0.03)	(0.06)					
Operational costs	-0.837***	-1.636***	-1.756***	-1.218***	-2.2835	-2.7074	-6.1227	-2.6751	-3.737
(in 100zł/100km)	(0.14)	(0.16)	(0.24)	(0.35)	(0.4)	(0.291)	(1.039)	(0.791)	(0.663)
Driving range	0.093***	0.142***	0.108***	0.123***	0.2546	0.2357	0.3762	0.2704	0.2884
(in 100km)	(0.01)	(0.01)	(0.02)	(0.02)	(0.024)	(0.021)	(0.069)	(0.055)	(0.045)
Refuelling/recharging time	-0.001	-0.024	0.028	0.046	-0.0016b	-0.0405b	0.099b	0.1002b	0.0428
	(0.02)	(0.03)	(0.05)	(0.07)	(0.052)	(0.049)	(0.169)	(0.146)	(0.114)
Refuelling/recharging time x BEV	-0.051**	-0.075*	-0.094	-0.131*	-0.1397	-0.1241	-0.3291b	-0.287	-0.2336
	(0.02)	(0.04)	(0.06)	(0.08)	(0.066)	(0.069)	(0.204)	(0.181)	(0.143)
Fast-mode recharging 2	0.252***	0.387***	0.345**	0.323	0.688	0.6402	1.204	0.7089b	0.8314
	(0.05)	(0.08)	(0.13)	(0.21)	(0.148)	(0.133)	(0.47)	(0.465)	(0.332)
Fast-mode recharging 3	0.425***	0.524***	0.522***	0.719***	1.1599	0.8666	1.8192	1.5784	1.362
	(0.05)	(0.08)	(0.13)	(0.19)	(0.155)	(0.13)	(0.478)	(0.453)	(0.329)
Fast-mode recharging 2 x BEV	0.063	0.112	-0.042	0.172	0.1713b	0.1854b	-0.1463b	0.3787b	0.1399
	(0.08)	(0.16)	(0.16)	(0.34)	(0.209)	(0.257)	(0.566)	(0.74)	(0.491)
Fast-mode recharging 3 x BEV	0.121*	0.494***	-0.028	0.344	0.3312	0.8171	-0.0967b	0.7553b	0.5197
	(0.07)	(0.15)	(0.15)	(0.31)	(0.19)	(0.252)	(0.529)	(0.681)	(0.461)
Free parking	0.148***	0.243***	0.155***	0.252**	0.4048	0.4017	0.539	0.5542	0.4873
	(0.02)	(0.04)	(0.05)	(0.1)	(0.064)	(0.064)	(0.172)	(0.219)	(0.142)
Free public transport	0.109***	0.144***	0.101**	0.126	0.2964	0.2384	0.3518	0.2763b	0.2837
	(0.02)	(0.04)	(0.05)	(0.1)	(0.069)	(0.063)	(0.178)	(0.211)	(0.141)
HEV	-0.897***	0.493***	-0.589***	-3.097***	-2.4491	0.816	-2.0543	-6.8003	-2.2614
	(0.05)	(0.06)	(0.1)	(0.13)	(0.241)	(0.112)	(0.431)	(0.889)	(0.434)
PHEV	-0.699***	0.587***	-0.251*	-3.159***	-1.9078	0.9715	-0.8747	-6.9373	-1.8782
	(0.07)	(0.09)	(0.15)	(0.22)	(0.241)	(0.155)	(0.518)	(0.998)	(0.509)
BEV	-0.444***	-0.865***	1.303***	-3.407***	-1.2125	-1.4313	4.5418	-7.4813	-1.3565
	(0.09)	(0.18)	(0.16)	(0.33)	(0.265)	(0.299)	(0.751)	(1.089)	(0.665)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

(Continued)

Table 5.6: Continued

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class assignment parameters									
City center		-0.189	-0.22	0					
		(0.19)	(0.2)						
Suburbs		-0.06	-0.114	0					
		(0.17)	(0.18)						
Family house		-0.039	0.319*	0					
		(0.17)	(0.18)						
Garage at home		0.017	-0.103	0					
		(0.14)	(0.16)						
Missing income		0.401	0.306	0					
		(0.27)	(0.29)						
Household income		0.393*	0.267	0					
		(0.22)	(0.24)						
Diesel		0.073	0.036	0					
		(0.14)	(0.15)						
AFV		0.326**	0.692***	0					
		(0.14)	(0.15)						
Personal norms		0.021	0.039	0					
		(0.02)	(0.03)						
Technophilia		0.026	-0.002	0					
		(0.02)	(0.02)						
Multicar		-0.323**	-0.292**	0					
		(0.14)	(0.15)						
Social group		1.14***	1.635***	0					
		(0.32)	(0.31)						
Constant		-0.164	-0.597**	0					
		(0.27)	(0.29)						
Class probabilities		0.41	0.31	0.29					
LL	-17,181.7	-13,954.9							
df	14	68							
AIC	34,391.4	28,045.7							
BIC	34,515.8	28,649.8							
N	53,248	53,248							
N respondents	1,664	1,664							

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Table 5.7: Model with 5 latent classes using all data from Sample A (Std. Errors in paretheses)

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class-specific parameters													
Purchase price	-0.366***	-0.293***	-0.053	-0.398***	-1.072***	-0.29***							
(in 10,000zł)	(0.03)	(0.04)	(0.09)	(0.06)	(0.07)	(0.05)							
Operational costs	-0.837***	-0.773**	-0.51	-2.011***	-2.398***	-1.462***	-2.2835	-2.6377	-9.6628b	-5.0467	-2.2371	-5.0505	-4.9154
(in 100zł/100km)	(0.14)	(0.29)	(0.58)	(0.29)	(0.25)	(0.41)	(0.4)	(0.978)	(19.061)	(1.041)	(0.248)	(1.561)	(4.871)
Driving range	0.093***	0.088***	0.098**	0.112***	0.167***	0.154***	0.2546	0.3015	1.8485b	0.2818	0.1561	0.5319	0.6218
(in 100km)	(0.01)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.024)	(0.089)	(3.23)	(0.061)	(0.015)	(0.144)	(0.767)
Refuelling/recharging time	-0.001	-0.042	-0.064	0.022	0.054	-0.201*	-0.0016b	-0.1419b	-1.217b	0.0562b	0.0508b	-0.6957	-0.3298
	(0.02)	(0.06)	(0.16)	(0.06)	(0.04)	(0.1)	(0.052)	(0.203)	(3.843)	(0.146)	(0.039)	(0.377)	(0.97)
Refuelling/recharging time x BEV	-0.051**	-0.003	0.016	-0.076	-0.219***	0.19	-0.1397	-0.0105b	0.3012b	-0.191b	-0.2044	0.6567b	0.0218
	(0.02)	(0.08)	(0.17)	(0.07)	(0.05)	(0.12)	(0.066)	(0.286)	(3.37)	(0.175)	(0.051)	(0.433)	(0.893)
Fast-mode recharging 2	0.252***	0.533***	0.404	0.351**	0.301**	-0.148	0.688	1.8203	7.6538b	0.8814	0.281	-0.5095b	2.2249
	(0.05)	(0.14)	(0.48)	(0.16)	(0.12)	(0.29)	(0.148)	(0.532)	(15.269)	(0.42)	(0.111)	(1.013)	(3.715)
Fast-mode recharging 3	0.425***	0.714***	0.949**	0.492**	0.618***	0.393	1.1599	2.4371	17.9868b	1.2342	0.5764	1.3557b	4.9695
	(0.05)	(0.14)	(0.42)	(0.16)	(0.11)	(0.25)	(0.155)	(0.59)	(32.179)	(0.445)	(0.104)	(0.864)	(7.485)
Fast-mode recharging 2 x BEV	0.063	0.047	-0.212	-0.023	0.216	0.555	0.1713b	-0.2377b	-4.0102b	-0.0578b	0.2016b	1.9175b	-0.6446
	(0.08)	(0.27)	(0.63)	(0.19)	(0.2)	(0.46)	(0.209)	(0.203)	(13.816)	(0.488)	(0.185)	(1.629)	(3.543)
Fast-mode recharging 3 x BEV	0.121*	0.219	-0.099	0.005	0.357*	0.699*	0.3312	-0.0418b	-1.8834b	0.0122b	0.3331	2.416	0.0184
	(0.07)	(0.26)	(0.56)	(0.18)	(0.2)	(0.38)	(0.19)	(0.402)	(11.439)	(0.451)	(0.187)	(1.423)	(2.98)
Free parking	0.148***	0.361***	0.55**	0.139**	0.184***	0.117	0.4048	1.2309	10.4263b	0.3494	0.1716	0.4044b	2.6803
	(0.02)	(0.07)	(0.19)	(0.06)	(0.05)	(0.1)	(0.064)	(0.313)	(18.949)	(0.148)	(0.051)	(0.351)	(4.356)
Free public transport	0.109***	0.228**	0.226	0.079	0.093	0.279**	0.2964	0.7785	4.2875b	0.198b	0.0868b	0.965	1.2362
	(0.02)	(0.07)	(0.17)	(0.06)	(0.06)	(0.1)	(0.069)	(0.282)	(7.995)	(0.151)	(0.055)	(0.386)	(1.914)
HEV	-0.897***	0.882***	-4.049***	-0.45***	-0.844***	1.698***	-2.4491	3.0104	-76.7441b	-1.129	-0.7878	5.8664	-16.6206
	(0.05)	(0.17)	(0.29)	(0.12)	(0.11)	(0.19)	(0.241)	(0.707)	(134.115)	(0.337)	(0.116)	(1.27)	(30.249)
PHEV	-0.699***	1.912***	-4.587***	-0.164	-0.657***	0.349	-1.9078	6.5232	-86.9516b	-0.4117b	-0.6133	1.2053b	-18.5957
	(0.07)	(0.2)	(0.47)	(0.18)	(0.14)	(0.28)	(0.241)	(1.17)	(151.815)	(0.458)	(0.143)	(0.997)	(34.276)
BEV	-0.444***	0.329	-4.101***	1.495***	-1.298***	-1.037**	-1.2125	-1.7316b	-77.7353b	3.752	-1.2108	-3.5808	-16.9334
	(0.09)	(0.33)	(0.53)	(0.2)	(0.25)	(0.48)	(0.265)	(1.456)	(134.386)	(0.709)	(0.255)	(1.692)	(30.55)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

(Continued)

Table 5.7: Continued

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class assignment parameters													
City center		0.322	0.354	0.149	0.219	0							
		(0.36)	(0.32)	(0.32)	(0.32)								
Suburbs		0.463	0.205	0.13	0.029	0							
		(0.33)	(0.3)	(0.29)	(0.3)								
Family house		-0.08	0.176	0.41	0.314	0							
		(0.31)	(0.28)	(0.28)	(0.29)								
Garage at home		0.048	0.123	-0.068	0.029	0							
		(0.27)	(0.24)	(0.24)	(0.25)								
Missing income		-0.197	-0.546	-0.262	-0.234	0							
		(0.48)	(0.41)	(0.4)	(0.41)								
Household income		0.612	-0.161	0.053	0.016	0							
		(0.43)	(0.4)	(0.4)	(0.42)								
Diesel		-0.011	-0.114	-0.104	-0.047	0							
		(0.26)	(0.23)	(0.23)	(0.24)								
AFV		0.628**	-0.053	0.636**	0.05	0							
		(0.27)	(0.24)	(0.24)	(0.25)								
Personal norms		0.051	-0.011	0.031	-0.017	0							
		(0.05)	(0.04)	(0.04)	(0.04)								
Technophilia		-0.006	-0.029	-0.026	-0.005	0							
		(0.04)	(0.04)	(0.04)	(0.04)								
Multicar		-0.112	0.224	0.01	0.11	0							
		(0.27)	(0.24)	(0.24)	(0.24)								
Social group		-0.108	-1.779***	0.049	-1.478***	0							
		(0.37)	(0.44)	(0.32)	(0.42)								
Constant		-0.472	1.004**	0.533	1.113**	0							
		(0.51)	(0.45)	(0.45)	(0.46)								
Class probabilities		0.15	0.22	0.25	0.29	0.10							
LL	-17,181.7	-13,419.2											
df	14	122											
AIC	34,391.4	27,082.4											
BIC	34,515.8	28,166.1											
N	53,248	53,248											
N respondents	1,664	1,664											

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

have the opportunity to park their car at a garage at their home, even though are less likely to live in a family house. Both groups are again found to be surrounded by other people, who consider buying an electric vehicle.

Model with 5 latent classes supports the results of the previous model and adds subtler aspects. Those in favour of hybrid vehicles, but also those with weaker preferences for conventional vehicles, are found to favour new technologies significantly more than those strongly preferring conventional vehicles. Those preferring plug-in electric vehicles are again more likely to be surrounded by like-minded people, and the group mostly preferring battery electric vehicles is also found to be significantly more likely to own two or more vehicles.

Regarding the estimated parameters from the utility part of the LC models substantial differences can be found. In the model with 3 latent classes using Sample A data, the group in favour of hybrid vehicles is found to be discouraged by longer recharging time of a battery electric vehicle, which might be one of the reasons of their preference for hybrid vehicles. On the contrary, respondents preferring battery electric vehicles do not find the refuelling/recharging time attribute significant. Both hybrid and battery electric vehicles preferring groups are found to be significantly positively influenced by both free parking and free public transport incentives.

These results are confirmed when looking at the results from LC model with 5 latent classes. Those favouring hybrid vehicles value higher availability of fast-mode recharging stations significantly more, and those in favour of battery electric vehicles do not find the refuelling/recharging attribute significant. In addition, it was found that those in strong opposition to any electric vehicle find most attributes insignificant, also purchase price and operational costs attributes, which might indicate their unwillingness to consider any vehicle type other than their conventional standard.

In Sample B only those in favour of hybrid vehicles are found to be discouraged by refuelling/recharging time attribute, as uncovered by a model with 3 latent classes, which is confirmed only for those preferring plug-in hybrid electric vehicles when considering model with 5 latent classes. Interestingly, only those in favour of hybrid vehicles are found to be influenced by free public transport incentive, as suggested by model with 5 latent classes, although this attribute was surprisingly significant only in the group with strong preferences for conventional vehicles when assuming only 3 latent classes.

Even when the attributes parameters are found significant, the sensitivities for each attribute differ between classes in both samples. The most sensitive to

Table 5.8: Model with 3 latent classes using all data from Sample B (Std. Errors in paretheses)

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class-specific parameters									
Purchase price	-0.428***	-0.249***	-0.72***	-0.566***					
(in 10,000zł)	(0.07)	(0.05)	(0.07)	(0.12)					
Operational costs	-0.76**	-0.918**	-1.606***	-0.711	-1.7744	-3.6858	-2.2303	-1.2559b	-2.3687
(in 100zł/100km)	(0.26)	(0.33)	(0.31)	(0.66)	(0.634)	(1.527)	(0.476)	(1.17)	(1.029)
Driving range	0.094***	0.104***	0.138***	0.102**	0.219	0.4182	0.192	0.1807	0.2589
(in 100km)	(0.01)	(0.03)	(0.02)	(0.03)	(0.042)	(0.147)	(0.035)	(0.071)	(0.082)
Refuelling/recharging time	-0.029*	0.016	-0.053*	-0.065	-0.0668	0.0653b	-0.074	-0.1144b	-0.0436
	(0.02)	(0.03)	(0.03)	(0.06)	(0.035)	(0.118)	(0.043)	(0.101)	(0.085)
Fast-mode recharging 2	0.373***	0.459***	0.517***	0.241	0.8705	1.8423	0.7179	0.4258b	0.9741
	(0.07)	(0.13)	(0.13)	(0.23)	(0.204)	(0.625)	(0.192)	(0.407)	(0.397)
Fast-mode recharging 3	0.417***	0.512***	0.587***	0.343	0.973	2.0566	0.8153	0.6059b	1.1347
	(0.07)	(0.14)	(0.13)	(0.23)	(0.197)	(0.658)	(0.188)	(0.404)	(0.405)
Free parking	0.178***	0.196**	0.329***	0.064	0.4147	0.7872	0.4571	0.1125b	0.4484
	(0.04)	(0.09)	(0.07)	(0.15)	(0.118)	(0.398)	(0.112)	(0.271)	(0.253)
Free public transport	0.091**	-0.014	0.084	0.369**	0.2135	-0.0569b	0.1172b	0.6521	0.2362
	(0.04)	(0.09)	(0.07)	(0.15)	(0.102)	(0.348)	(0.097)	(0.313)	(0.245)
HEV	-0.879***	-0.702***	0.867***	-3.051***	-2.0536	-2.8197	1.2042	-5.3865	-2.1866
	(0.1)	(0.19)	(0.15)	(0.22)	(0.424)	(0.999)	(0.249)	(1.286)	(0.819)
PHEV	-0.717***	-0.278	0.844***	-2.516***	-1.6757	-1.1167b	1.172	-4.4427	-1.3612
	(0.1)	(0.19)	(0.17)	(0.24)	(0.35)	(0.789)	(0.275)	(1.074)	(0.694)
BEV	-0.484**	1.18***	-0.694**	-2.785***	-1.1298	4.7374	-0.9641	-4.9174	-0.4661
	(0.18)	(0.27)	(0.29)	(0.47)	(0.448)	(1.494)	(0.406)	(1.361)	(1.055)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

(Continued)

Table 5.8: Continued

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class assignment parameters									
City center		0.411 (0.41)	1.012** (0.39)	0					
Suburbs		0.107 (0.36)	0.72** (0.34)	0					
Family house		-0.685* (0.36)	-0.28 (0.33)	0					
Garage at home		0.606** (0.29)	0.338 (0.29)	0					
Missing income		-1.15* (0.61)	-0.725 (0.55)	0					
Household income		-0.835 (0.57)	-0.013 (0.52)	0					
Diesel		0.021 (0.28)	-0.006 (0.27)	0					
AFV		0.593** (0.27)	0.431 (0.26)	0					
Personal norms		0.06 (0.05)	0.029 (0.04)	0					
Technophilia		0.035 (0.05)	0.088** (0.04)	0					
Multicar		0.323 (0.29)	0.025 (0.3)	0					
Social group		1.628** (0.59)	1.51** (0.58)	0					
Constant		-1.063* (0.63)	-1.81** (0.6)	0					
Class probabilities		0.31	0.36	0.32					
LL	-4,941.4	-3,954.6							
df	11	59							
AIC	9,904.9	8,027.2							
BIC	9,988.9	8,477.6							
N	15,264	15,264							
N respondents	477	477							

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Table 5.9: Model with 5 latent classes using all data from Sample B (Std. Errors in paretheses)

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class-specific parameters													
Purchase price	-0.428***	-0.481***	-0.148**	-0.697***	-1.062***	-0.445*							
(in 10,000zł)	(0.07)	(0.1)	(0.06)	(0.09)	(0.13)	(0.23)							
Operational costs	-0.76**	-0.493	-0.613	1.924***	-7.5***	0	-1.7744	-1.0255b	-4.1426b	2.7612	-7.0625	-0.001b	-1.8901
(in 100zł/100km)	(0.26)	(0.68)	(0.51)	(0.39)	(0.84)	(1.26)	(0.634)	(1.403)	(3.653)	(0.569)	(1.081)	(2.829)	(1.956)
Driving range	0.094***	0.017	0.11**	0.124***	0.202***	0.145**	0.219	0.0355b	0.7411	0.178	0.1902	0.3268	0.3174
(in 100km)	(0.01)	(0.05)	(0.03)	(0.04)	(0.03)	(0.07)	(0.042)	(0.109)	(0.378)	(0.056)	(0.037)	(0.236)	(0.169)
Refuelling/recharging time	-0.029*	-0.129*	-0.076*	0.04	0.026	-0.007	-0.0668	-0.2684	-0.5151	0.0579b	0.0243b	-0.0161b	-0.129
	(0.02)	(0.07)	(0.04)	(0.04)	(0.05)	(0.13)	(0.035)	(0.157)	(0.32)	(0.056)	(0.049)	(0.284)	(0.176)
Fast-mode recharging 2	0.373***	0.187	0.434**	0.531**	0.871***	0.388	0.8705	0.3884b	2.9336	0.7613	0.8204	0.872b	1.2174
	(0.07)	(0.27)	(0.19)	(0.18)	(0.26)	(0.51)	(0.204)	(0.575)	(1.664)	(0.255)	(0.261)	(1.216)	(0.817)
Fast-mode recharging 3	0.417***	0.038	0.541***	0.629***	1.207***	0.368	0.973	0.0792b	3.6565	0.903	1.1367	0.8276b	1.4221
	(0.07)	(0.27)	(0.17)	(0.18)	(0.24)	(0.43)	(0.197)	(0.572)	(1.782)	(0.26)	(0.261)	(1.011)	(0.796)
Free parking	0.178***	0.358**	0.296**	0.203**	0.256**	-0.23	0.4147	0.7443	2.0018	0.2913	0.2412	-0.5162b	0.5173
	(0.04)	(0.17)	(0.12)	(0.1)	(0.12)	(0.28)	(0.118)	(0.38)	(1.149)	(0.149)	(0.115)	(0.693)	(0.509)
Free public transport	0.091**	0.379**	0.096	0.033	0.198*	0.327	0.2135	0.7882	0.648b	0.0477b	0.1868	0.734b	0.4537
	(0.04)	(0.16)	(0.12)	(0.1)	(0.11)	(0.27)	(0.102)	(0.356)	(0.852)	(0.147)	(0.102)	(0.695)	(0.439)
HEV	-0.879***	0.512	-2.105***	0.682**	1.215***	-3.404***	-2.0536	1.0637b	-14.2294	0.9789	1.1438	-7.6486	-4.2071
	(0.1)	(0.32)	(0.27)	(0.27)	(0.2)	(0.37)	(0.424)	(0.705)	(6.246)	(0.395)	(0.236)	(4.316)	(2.549)
PHEV	-0.717***	2.46***	-1.063***	0.425	-0.547**	-3.505***	-1.6757	5.1124	-7.184	0.6094b	-0.5148	-7.8751	-2.6853
	(0.1)	(0.37)	(0.22)	(0.29)	(0.27)	(0.5)	(0.35)	(1.214)	(3.297)	(0.427)	(0.258)	(4.357)	(2.002)
BEV	-0.484**	0.129	-0.316	3.524***	-4.043***	-3.91***	-1.1298	0.269b	-2.1382b	5.0571	-3.8067	-8.7839	-2.1165
	(0.18)	(0.62)	(0.36)	(0.43)	(0.59)	(0.91)	(0.448)	(1.293)	(2.58)	(0.763)	(0.685)	(5.049)	(2.181)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%

(Continued)

Table 5.9: Continued

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class assignment parameters													
City center		1.391**	0.21	0.548	1.155**	0							
		(0.62)	(0.53)	(0.49)	(0.51)								
Suburbs		0.988*	0.153	0.262	0.661	0							
		(0.57)	(0.47)	(0.43)	(0.43)								
Family house		-0.8	-1.142**	-0.84**	0.01	0							
		(0.5)	(0.48)	(0.43)	(0.44)								
Garage at home		0.865**	0.816**	0.592*	0.164	0							
		(0.43)	(0.4)	(0.36)	(0.37)								
Missing income		-1.192	-2.018*	-1.387**	-0.519	0							
		(0.89)	(1.04)	(0.7)	(0.64)								
Household income		0.056	0.021	-0.784	0.67	0							
		(0.81)	(0.7)	(0.75)	(0.61)								
Diesel		0.25	-0.506	-0.061	-0.255	0							
		(0.38)	(0.37)	(0.33)	(0.34)								
AFV		0.165	-0.033	0.488	0.57*	0							
		(0.4)	(0.36)	(0.32)	(0.33)								
Personal norms		0.036	-0.055	0.065	0.021	0							
		(0.07)	(0.06)	(0.06)	(0.06)								
Technophilia		0.171**	0.118**	0.093	0.109*	0							
		(0.07)	(0.06)	(0.06)	(0.06)								
Multicar		-0.211	0.796**	0.71**	0.48	0							
		(0.49)	(0.39)	(0.36)	(0.37)								
Social group		1.612**	0.007	1.578**	0.741	0							
		(0.67)	(0.81)	(0.62)	(0.68)								
Constant		-3.655***	-0.613	-1.688**	-2.47***	0							
		(0.97)	(0.71)	(0.73)	(0.77)								
Class probabilities		0.26	0.22	0.28	0.17	0.07							
LL	-4,941.4	-3,786.0											
df	11	107											
AIC	9,904.9	7,786.0											
BIC	9,988.9	8,602.7											
N	15,264	15,264											
N respondents	477	477											

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%

purchase price attributes are those stating their preference for hybrid technologies, and this group would also value higher driving range more. The differences in parameters estimates in both samples can be seen better when looking at the individual-level densities obtained from models with 5 latent classes, which can be found in Appendix C.

Regarding the willingness-to-pay estimates, there is high variability among the classes in both models, as can be seen in respective tables. In order to compare the estimated values with those from previous studies, probability weighted averages will be taken into account. To convert the estimated values into euros, the average exchange rate for year 2014, €1 = 4.18zł was applied.

Starting with operational costs the average willingness-to-pay for cost savings of €1/100km in Sample A was found to be €89.4 and €117.6 from model with 3 and 5 classes, respectively, while in Sample B the values found were €56.7 and €45.2 in the same order. These results are at the low end of the wide range of estimates foud previously. Jensen *et al.* (2013) report values ranging from €79-200, while Hackbarth & Madlener (2013) find values as high as €530-1070.

Regarding 1km of additional driving range, the estimated WTP values in Sample A were found €6.9 and €14.9, when 3 and 5 latent classes were assumed, respectively. In Sample B the values found were €6.2 and €7.6. These values are in line with those found earlier. Hoen & Koetse (2014) report values ranging from €8-33, while Jensen *et al.* (2013) find range as wide as €3-134.

As for the battery recharging time, in Sample A the estimates range from €5.6 when 3 classes to €7.4 when 5 classes were assumed for every save hour in recharging. The values for Sample B range as low as €1.1 to €3.1. These estimates are extremely low, as in previous studies similar and higher ranges were found, but for one minute saved. For every minute saved in recharging Hackbarth & Madlener (2013) state WTP values of €5-18, while Hoen & Koetse (2014) report values as high as €24-182.

Respondents in Sample A value the increase in fast-mode recharging infrastructure for BEVs from low to medium at values of €2323.7 when 3 latent classes and €3,780.6 when 5 latent classes are considered. The increase from low to high in this group ranges between €4,501.7 to €11,932.8. For Sample B the values to medium increase are found between €2,330.4 to 2,912.4, and an increase to high availability in the range of €2,714.6 to €3,402.2. In the previous studies increase in the availability of fast-mode recharging stations was not particularly studied, but WTP value for 1% expansion of the refuelling infrastructure as such was found in the range of €45-92 in Hackbarth & Madlener (2013) and between €70-820 in Achtnicht (2012).

The willingness-to-pay for the free public transport incentive was found in the ranges between €678.7 and €2857.4, and €565.1 to €1,085.4 in Sample A and Sample B, respectively. For the free parking respondents in Sample A are willing to pay between €1,165.8 and €6,412.2 when 3 and 5 latent classes are assumed, respectively. In Sample B these values range from €1,072.7 to €1,237.6. The values are higher than previously found, as Hoen & Koetse (2014) found WTP as low as €377 for this incentive, and Hess *et al.* (2012) report values in the range of €394 to €1,415.

As for the electricity fuel type technology itself, respondents in Sample A would on average require a compensation of €5,410.1, €4,493.3 and €3,245.2 to switch from conventional technology to hybrid electric, plug-in hybrid electric, and pure electric, respectively. In Sample B these values are estimated to be €5,231.1, €3,256, and €1,115.1, respectively. These weighted averages suggest that compensations to change to EVs would be necessary, even though there were segments of respondents uncovered, who would actually be willing to pay for this switch. These WTP estimates for hybrid electric vehicles range from €1,952 to €14,034.5 in Sample A, and from €2,736.4 to €2,880,9. For plug-in hybrid electric vehicles the ranges of WTPs are €2,324.2 to €15,605,7, and €280,4 to €12,230.6 in Sample A and Sample B, respectively. For the battery electric vehicles the WTP values range from €8,976.1 to €10,865.6 in Sample A, and from €11,333,5 to €12,098.3 in Sample B.

In addition, in order to uncover the likely differences between those who intend to buy new and used vehicles, models for these two groups of respondents using Sample A data were estimated separately. These results are shown in Table 5.10, Table 5.11, Table 5.12 and Table 5.13.

As would be expected, used car buyers are generally much more sensitive to purchase price than those expecting to buy a brand new vehicle. As a result, the willingess-to-pay estimates of those intending to buy a used vehicle for all attributes are much lower than of those intending to purchase a brand new car. New car buyers are, however, much more sensitive to increases in operational costs.

Table 5.10: Model with 3 latent classes using data on new car buyers in Sample A (Std. Errors in paretheses)

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class-specific parameters									
Purchase price	-0.267***	-0.522***	-0.194*	-0.162***					
(in 10,000zł)	(0.03)	(0.04)	(0.12)	(0.03)					
Operational costs	-1.066***	-2.417***	-2.517**	-1.954***	-3.9885	-4.6265	-12.987	-12.0575	-9.3426
(in 100zł/100km)	(0.3)	(0.43)	(0.86)	(0.46)	(1.162)	(0.845)	(7.752)	(3.565)	(3.637)
Driving range	0.086***	0.145***	0.122**	0.083**	0.3207	0.2776	0.6275	0.512	0.4502
(in 100km)	(0.01)	(0.02)	(0.05)	(0.03)	(0.059)	(0.048)	(0.417)	(0.209)	(0.202)
Refuelling/recharging time	-0.063*	-0.185**	0.402**	0.015	-0.2363	-0.3542	2.0727	0.0944b	0.4629
	(0.04)	(0.06)	(0.2)	(0.09)	(0.136)	(0.121)	(1.954)	(0.529)	(0.76)
Refuelling/recharging time x BEV	0.036	0.156*	-0.274	-0.099	0.1355b	0.2993	-1.4133b	-0.6105b	-0.469
	(0.04)	(0.09)	(0.22)	(0.1)	(0.166)	(0.173)	(1.686)	(0.648)	(0.745)
Fast-mode recharging 2	0.176*	0.32*	1.102**	0.113	0.6583	0.6131	5.6894	0.6986b	2.0468
	(0.09)	(0.17)	(0.47)	(0.23)	(0.362)	(0.326)	(4.166)	(1.387)	(1.732)
Fast-mode recharging 3	0.191**	0.364**	0.471	0.316	0.714	0.6972	2.4297b	1.9491b	1.5815
	(0.1)	(0.17)	(0.53)	(0.22)	(0.365)	(0.317)	(2.698)	(1.404)	(1.327)
Fast-mode recharging 2 x BEV	0.012	0.016	-2.913**	0.3	0.0435b	0.0312b	-15.0324	1.848b	-3.5546
	(0.16)	(0.36)	(0.95)	(0.29)	(0.592)	(0.697)	(10.722)	(1.805)	(3.832)
Fast-mode recharging 3 x BEV	0.285**	0.475	-0.614	0.235	1.0678	0.91b	-3.1685b	1.4517b	-0.0448
	(0.14)	(0.33)	(0.72)	(0.27)	(0.529)	(0.634)	(3.835)	(1.681)	(1.859)
Free parking	0.136**	0.235**	-0.185	0.21**	0.5104	0.4494	-0.9526b	1.2961	0.3345
	(0.04)	(0.08)	(0.24)	(0.08)	(0.176)	(0.16)	(1.459)	(0.578)	(0.655)
Free public transport	0.112**	0.016	-0.092	0.274**	0.4182	0.03b	-0.474b	1.6886	0.4261
	(0.05)	(0.08)	(0.23)	(0.09)	(0.19)	(0.158)	(1.203)	(0.664)	(0.611)
HEV	-0.842***	0.511***	-2.84***	-0.166	-3.1505	0.9778	-14.6563	-1.0243b	-3.9995
	(0.11)	(0.14)	(0.27)	(0.18)	(0.61)	(0.271)	(9.133)	(1.133)	(3.004)
PHEV	-0.383**	1.069***	-3.953***	0.138	-1.4338	2.0469	-20.4007	0.8529b	-4.5567
	(0.13)	(0.19)	(0.64)	(0.25)	(0.538)	(0.391)	(13.93)	(1.537)	(4.511)
BEV	-0.689***	-1.588***	-4.149***	1.054***	-2.5782	-3.0395	-21.4092	6.5035	-5.0455
	(0.19)	(0.43)	(0.77)	(0.31)	(0.75)	(0.837)	(12.933)	(2.308)	(4.663)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

(Continued)

Table 5.10: Continued

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class assignment parameters									
City center		0.154	1.135**	0					
		(0.41)	(0.46)						
Suburbs		0.01	1.071**	0					
		(0.34)	(0.39)						
Family house		-0.6*	-0.24	0					
		(0.36)	(0.37)						
Garage at home		0.747**	0.356	0					
		(0.32)	(0.32)						
Missing income		1	0.333	0					
		(0.62)	(0.7)						
Household income		0.007	-0.32	0					
		(0.37)	(0.39)						
Diesel		-0.062	-0.041	0					
		(0.3)	(0.31)						
AFV		-0.315	-0.562*	0					
		(0.3)	(0.32)						
Personal norms		-0.052	-0.062	0					
		(0.05)	(0.05)						
Technophilia		0.065	0.028	0					
		(0.05)	(0.05)						
Multicar		0.093	0.245	0					
		(0.29)	(0.3)						
Social group		-0.364	-1.466**	0					
		(0.42)	(0.55)						
Constant		-0.135	-0.535	0					
		(0.59)	(0.6)						
Class probabilities		0.40	0.28	0.32					
LL	-4,101.9	-3,255.6							
df	14	68							
AIC	8,231.8	6,647.2							
BIC	8,336.2	7,154.1							
N	12,768	12,768							
N respondents	399	399							

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Table 5.11: Model with 5 latent classes using data on new car buyers in Sample A (Std. Errors in paretheses)

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class-specific parameters													
Purchase price	-0.267***	-1.301***	-0.024	-0.016	-0.253***	-0.333***							
(in 10,000zł)	(0.03)	(0.13)	(0.08)	(0.12)	(0.05)	(0.05)							
Operational costs	-1.066***	-7.338***	-0.253	-0.144	-2.096***	-1.282**	-3.9885	-5.6385	-10.4048b	-8.744b	-8.2786	-3.8455	-7.1402
(in 100zł/100km)	(0.3)	(1.11)	(1.1)	(1.29)	(0.52)	(0.58)	(1.162)	(0.819)	(42.344)	(92.911)	(2.557)	(1.814)	(25.859)
Driving range	0.086***	0.246***	0.146**	0.109	0.067*	0.115**	0.3207	0.1893	5.9844b	6.6186b	0.264	0.344	2.2416
(in 100km)	(0.01)	(0.04)	(0.07)	(0.08)	(0.04)	(0.04)	(0.059)	(0.034)	(18.193)	(49.525)	(0.146)	(0.119)	(12.742)
Refuelling/recharging time	-0.063*	-0.287***	0.09	0.181	-0.079**	-0.031	-0.2363	-0.2204	3.7014b	11.0225b	-0.3139	-0.0944b	2.6361
	(0.04)	(0.08)	(0.09)	(0.15)	(0.03)	(0.04)	(0.136)	(0.059)	(13.29)	(82.284)	(0.141)	(0.127)	(19.383)
Refuelling/recharging time x BEV	0.036						0.1355b						
	(0.04)						(0.166)						
Fast-mode recharging 2	0.176*	0.204	0.493	-0.586	0.374**	0.367**	0.6583	0.1571b	20.2358b	-35.609b	1.4762	1.1002	-5.0105
	(0.09)	(0.31)	(0.31)	(0.72)	(0.17)	(0.19)	(0.362)	(0.237)	(66.122)	(269.505)	(0.733)	(0.561)	(65.928)
Fast-mode recharging 3	0.191**	0.314	0.454	0.307	0.5**	0.572**	0.714	0.2416b	18.6298b	18.6521b	1.975	1.7155	6.9374
	(0.1)	(0.3)	(0.33)	(0.55)	(0.19)	(0.19)	(0.365)	(0.232)	(62.705)	(140.793)	(0.898)	(0.614)	(37.572)
Fast-mode recharging 2 x BEV	0.012						0.0435b						
	(0.16)						(0.592)						
Fast-mode recharging 3 x BEV	0.285**						1.0678						
	(0.14)						(0.529)						
Free parking	0.136**	-0.07	0.26	0.232	0.176*	0.374***	0.5104	-0.0537b	10.6879b	14.0864b	0.6967	1.1214	4.5924
	(0.04)	(0.15)	(0.26)	(0.42)	(0.1)	(0.1)	(0.176)	(0.117)	(32.809)	(109.207)	(0.403)	(0.348)	(27.394)
Free public transport	0.112**	-0.135	0.154	0.169	0.236**	0.135	0.4182	-0.1039b	6.3377b	10.2439b	0.931	0.4042b	3.2055
	(0.05)	(0.15)	(0.24)	(0.39)	(0.1)	(0.11)	(0.19)	(0.118)	(24.998)	(80.071)	(0.468)	(0.33)	(20.251)
HEV	-0.842***	0.167	-1.462***	-4.256***	-0.231	2.346***	-3.1505	0.1283b	-60.0289b	-258.5583b	-0.9107b	7.036	-61.251
	(0.11)	(0.26)	(0.29)	(0.54)	(0.22)	(0.48)	(0.61)	(0.201)	(191.274)	(1924.787)	(0.934)	(1.667)	(439.957)
PHEV	-0.383**	0.333	-0.718	-4.791***	-0.008	2.633***	-1.4338	0.2559b	-29.4559b	-291.0311b	-0.0298b	7.896	-64.7319
	(0.13)	(0.3)	(0.61)	(0.71)	(0.25)	(0.45)	(0.538)	(0.231)	(110.86)	(2168.893)	(0.984)	(1.708)	(484.917)
BEV	-0.689***	-3.093***	-1.973**	-4.614***	1.125**	1.213*	-2.5782	-2.3768	-81.005b	-280.2602b	4.443	3.6387	-67.9089
	(0.19)	(0.7)	(0.83)	(1.06)	(0.36)	(0.63)	(0.75)	(0.537)	(255.519)	(2078.877)	(1.521)	(1.898)	(480.439)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%

(Continued)

Table 5.11: Continued

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class assignment parameters													
City center		0.662	2.196**	1.199**	0.41	0							
		(0.59)	(0.93)	(0.56)	(0.53)								
Suburbs		-0.205	1.52*	0.89*	-0.135	0							
		(0.52)	(0.9)	(0.46)	(0.44)								
Family house		0.676	1.237*	0.562	0.91**	0							
		(0.5)	(0.68)	(0.43)	(0.43)								
Garage at home		-0.458	0.587	-0.008	-0.503	0							
		(0.44)	(0.73)	(0.39)	(0.38)								
Missing income		0.491	0.795	-0.388	-0.564	0							
		(0.78)	(0.9)	(0.75)	(0.75)								
Household income		0.362	-1.046	-0.34	-0.108	0							
		(0.48)	(0.8)	(0.46)	(0.45)								
Diesel		0.182	0.606	0.237	0.298	0							
		(0.45)	(0.55)	(0.39)	(0.4)								
AFV		-0.528	-1.275*	-0.639	0.008	0							
		(0.44)	(0.74)	(0.39)	(0.37)								
Personal norms		-0.042	0.113	-0.005	0.052	0							
		(0.07)	(0.09)	(0.06)	(0.06)								
Technophilia		0.046	-0.152*	-0.033	-0.052	0							
		(0.06)	(0.09)	(0.06)	(0.06)								
Multicar		-0.22	0.501	-0.03	-0.141	0							
		(0.4)	(0.59)	(0.36)	(0.37)								
Social group		-1.581**	-1.722	-1.772**	-0.381	0							
		(0.77)	(1.11)	(0.63)	(0.46)								
Constant		-0.37	-2.342*	-0.178	0.196	0							
		(0.8)	(1.35)	(0.72)	(0.72)								
Class probabilities		0.19	0.10	0.22	0.27	0.22							
LL	-4,101.9	-3,116.6											
df	14	107											
AIC	8,231.8	6,447.2											
BIC	8,336.2	7,244.8											
N	12,768	12,768											
N respondents	399	399											

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Table 5.12: Model with 3 latent classes using data on used car buyers in Sample A (Std. Errors in paretheses)

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class-specific parameters									
Purchase price	-0.589***	-0.826***	-0.311**	-0.854***					
(in 10,000zł)	(0.05)	(0.09)	(0.11)	(0.07)					
Operational costs	-0.669***	-1.525***	-0.702*	-1.271***	-1.1362	-1.8467	-2.2602	-1.489	-1.8427
(in 100zł/100km)	(0.18)	(0.32)	(0.4)	(0.21)	(0.318)	(0.408)	(1.418)	(0.271)	(0.679)
Driving range	0.101***	0.145***	0.127***	0.136***	0.1716	0.1757	0.408	0.1591	0.2437
(in 100km)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.033)	(0.165)	(0.022)	(0.071)
Refuelling/recharging time	0.023	-0.007	0.008	0.023	0.0385b	-0.0087b	0.0243b	0.0265b	0.0153
	(0.03)	(0.07)	(0.09)	(0.04)	(0.047)	(0.087)	(0.29)	(0.051)	(0.138)
Refuelling/recharging time x BEV	-0.071**	-0.022	-0.149	-0.122**	-0.1209	-0.0262b	-0.4789b	-0.1433	-0.2157
	(0.03)	(0.09)	(0.1)	(0.06)	(0.057)	(0.104)	(0.39)	(0.072)	(0.183)
Fast-mode recharging 2	0.286***	0.554**	0.083	0.369***	0.4862	0.6702	0.267b	0.4324	0.4506
	(0.08)	(0.2)	(0.27)	(0.11)	(0.136)	(0.243)	(0.882)	(0.134)	(0.406)
Fast-mode recharging 3	0.431***	0.664***	0.694**	0.412***	0.7318	0.8045	2.2348	0.4822	1.1394
	(0.07)	(0.19)	(0.24)	(0.11)	(0.134)	(0.244)	(1.089)	(0.13)	(0.471)
Fast-mode recharging 2 x BEV	0.118	-0.056	0.578	0.216	0.2008b	-0.068b	1.862b	0.2533b	0.672
	(0.11)	(0.24)	(0.39)	(0.21)	(0.188)	(0.291)	(1.374)	(0.249)	(0.621)
Fast-mode recharging 3 x BEV	0.146	-0.105	0.428	0.631**	0.2474b	-0.1265b	1.3789b	0.7388	0.6849
	(0.1)	(0.23)	(0.36)	(0.21)	(0.169)	(0.278)	(1.222)	(0.25)	(0.569)
Free parking	0.152***	0.151**	0.306**	0.219***	0.2578	0.1834	0.9851	0.2563	0.4677
	(0.03)	(0.07)	(0.12)	(0.05)	(0.054)	(0.085)	(0.509)	(0.063)	(0.212)
Free public transport	0.119***	0.096	0.201*	0.164**	0.2015	0.1162b	0.6487	0.1919	0.3155
	(0.03)	(0.07)	(0.12)	(0.05)	(0.058)	(0.09)	(0.447)	(0.064)	(0.194)
HEV	-1.005***	-0.631***	-3.257***	0.474***	-1.7071	-0.7642	-10.4864	0.5548	-3.3728
	(0.08)	(0.15)	(0.17)	(0.09)	(0.208)	(0.207)	(3.835)	(0.114)	(1.332)
PHEV	-0.871***	-0.321	-3.122***	0.52***	-1.4793	-0.3891b	-10.0514	0.6086	-3.1009
	(0.09)	(0.22)	(0.27)	(0.13)	(0.223)	(0.274)	(3.746)	(0.154)	(1.339)
BEV	-0.398**	1.44***	-2.693***	-0.687**	-0.6762	1.7432	-8.6707	-0.8052	-2.5602
	(0.13)	(0.24)	(0.36)	(0.24)	(0.229)	(0.342)	(3.13)	(0.289)	(1.214)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

(Continued)

Table 5.12: Continued

	Parameters				WTP				
	CL	LC			CL	LC			
		Class 1	Class 2	Class 3		Class 1	Class 2	Class 3	Weighted average
Class assignment parameters									
City center		0.081	-0.017	0					
		(0.28)	(0.27)						
Suburbs		-0.131	-0.396*	0					
		(0.25)	(0.24)						
Family house		0.414*	-0.151	0					
		(0.24)	(0.23)						
Garage at home		0.038	0.125	0					
		(0.22)	(0.21)						
Missing income		0.551	-0.47	0					
		(0.38)	(0.41)						
Household income		-0.188	-0.372	0					
		(0.41)	(0.39)						
Diesel		0	-0.133	0					
		(0.2)	(0.19)						
AFV		0.45**	-0.16	0					
		(0.2)	(0.19)						
Personal norms		0.027	-0.033	0					
		(0.03)	(0.03)						
Technophilia		-0.046	-0.021	0					
		(0.03)	(0.03)						
Multicar		-0.216	0.28	0					
		(0.21)	(0.19)						
Social group		0.501*	-1.25**	0					
		(0.3)	(0.45)						
Constant		-0.449	0.554	0					
		(0.41)	(0.38)						
Class probabilities		0.30	0.32	0.38					
LL	-8,843.1	-7,186.0							
df	14	68							
AIC	17,714.2	14,508.1							
BIC	17,829.4	15,067.4							
N	27,584	27,584							
N respondents	862	862							

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients at 10%

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Table 5.13: Model with 5 latent classes using data on used car buyers in Sample A (Std. Errors in paretheses)

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class-specific parameters													
Purchase price	-0.589***	-0.837***	-0.053	-1.101***	-1.262***	-0.132							
(in 10,000zł)	(0.05)	(0.09)	(0.18)	(0.13)	(0.13)	(0.09)							
Operational costs	-0.669***	-1.689***	-0.242	-1.555***	-1.168**	-0.946*	-1.1362	-2.0187	-4.5305b	-1.4127	-0.9256	-7.1659b	-3.3677
(in 100zł/100km)	(0.18)	(0.38)	(0.83)	(0.31)	(0.38)	(0.56)	(0.318)	(0.481)	(20.589)	(0.302)	(0.3)	(6.209)	(6.017)
Driving range	0.101***	0.138***	0.113**	0.168***	0.134***	0.106**	0.1716	0.1647	2.1078b	0.1527	0.1063	0.8055b	0.7121
(in 100km)	(0.01)	(0.03)	(0.05)	(0.02)	(0.03)	(0.05)	(0.02)	(0.036)	(7.061)	(0.025)	(0.026)	(0.635)	(1.672)
Refuelling/recharging time	0.023	-0.011	-0.226	0.057	0.029	-0.087	0.0385b	-0.0126b	-4.2331b	0.052b	0.0234b	-0.6578b	-1.0416
	(0.03)	(0.08)	(0.26)	(0.06)	(0.07)	(0.18)	(0.047)	(0.094)	(15.68)	(0.057)	(0.058)	(1.388)	(3.71)
Refuelling/recharging time x BEV	-0.071**	-0.008	0.142	-0.213**	-0.179	0.195	-0.1209	-0.0102b	2.6511b	-0.1935	-0.1416b	1.4776b	0.8316
	(0.03)	(0.1)	(0.28)	(0.08)	(0.11)	(0.2)	(0.057)	(0.114)	(10.957)	(0.074)	(0.088)	(1.722)	(2.788)
Fast-mode recharging 2	0.286***	0.549**	-0.385	0.392**	0.476**	0.071	0.4862	0.6562	-7.1973b	0.3565	0.377	0.5403b	-1.1771
	(0.08)	(0.21)	(0.78)	(0.19)	(0.2)	(0.52)	(0.136)	(0.253)	(29.427)	(0.173)	(0.164)	(3.944)	(7.304)
Fast-mode recharging 3	0.431***	0.637**	0.921	0.631***	0.446**	0.367	0.7318	0.7608	17.2307b	0.5733	0.3537	2.7801b	4.6195
	(0.07)	(0.2)	(0.57)	(0.17)	(0.2)	(0.51)	(0.134)	(0.251)	(58.174)	(0.162)	(0.166)	(4.186)	(13.51)
Fast-mode recharging 2 x BEV	0.118	-0.042	1.13	0.319	0.124	0.456	0.2008b	-0.0501b	21.1422b	0.2894b	0.0985b	3.4507b	5.3935
	(0.11)	(0.26)	(0.94)	(0.28)	(0.39)	(0.7)	(0.188)	(0.315)	(72.892)	(0.264)	(0.306)	(5.542)	(17.03)
Fast-mode recharging 3 x BEV	0.146	-0.036	0.021	0.498*	0.596	0.473	0.2474b	-0.0426b	0.3846b	0.4527	0.4727b	3.5851b	1.0983
	(0.1)	(0.25)	(0.8)	(0.27)	(0.39)	(0.63)	(0.169)	(0.296)	(15.01)	(0.259)	(0.308)	(5.225)	(4.568)
Free parking	0.152***	0.144*	0.421*	0.272***	0.278**	0.105	0.2578	0.1723	7.8862b	0.2475	0.2207	0.7962b	1.9927
	(0.03)	(0.07)	(0.26)	(0.08)	(0.09)	(0.16)	(0.054)	(0.091)	(26.843)	(0.073)	(0.074)	(1.359)	(6.099)
Free public transport	0.119***	0.118	0.437*	0.114	0.26**	0.095	0.2015	0.141b	8.1746b	0.1032b	0.2057	0.7197b	1.9978
	(0.03)	(0.08)	(0.25)	(0.08)	(0.1)	(0.16)	(0.058)	(0.099)	(27.592)	(0.079)	(0.079)	(1.315)	(6.252)
HEV	-1.005***	-0.451**	-4.122***	-1.219***	1.014***	1.625***	-1.7071	-0.5387	-77.1347b	-1.1071	0.8039	12.3075b	-13.8309
	(0.08)	(0.19)	(0.42)	(0.19)	(0.23)	(0.23)	(0.208)	(0.231)	(258.312)	(0.258)	(0.206)	(8.138)	(57.271)
PHEV	-0.871***	0.002	-4.336***	-1.142***	1.739***	-0.216	-1.4793	0.0019b	-81.1461b	-1.037	1.3786	-1.6346b	-17.6787
	(0.09)	(0.28)	(0.66)	(0.24)	(0.29)	(0.52)	(0.223)	(0.33)	(271.299)	(0.283)	(0.261)	(4.259)	(59.192)
BEV	-0.398**	1.621***	-4.008***	-1.031**	0.062	-1.02	-0.6762	1.9373	-75.012b	-0.9366	0.0488b	-7.7277b	-17.7816
	(0.13)	(0.3)	(0.75)	(0.34)	(0.45)	(0.64)	(0.229)	(0.425)	(249.279)	(0.346)	(0.359)	(6.913)	(55.134)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%
(Continued)

Table 5.13: Continued

	Parameters						WTP						
	CL	LC					CL	LC					
		Class 1	Class 2	Class 3	Class 4	Class 5		Class 1	Class 2	Class 3	Class 4	Class 5	Weighted average
Class assignment parameters													
City center		1.049**	1.043**	0.956*	1.602**	0							
		(0.52)	(0.52)	(0.53)	(0.57)								
Suburbs		0.125	-0.153	0.112	0.576	0							
		(0.4)	(0.41)	(0.42)	(0.47)								
Family house		0.673	0.178	0.395	0.34	0							
		(0.42)	(0.42)	(0.44)	(0.46)								
Garage at home		-0.336	-0.197	-0.284	-0.407	0							
		(0.38)	(0.39)	(0.4)	(0.43)								
Missing income		0.63	-0.195	-0.476	0.294	0							
		(0.67)	(0.7)	(0.77)	(0.79)								
Household income		0.884	0.678	0.652	1.714*	0							
		(0.82)	(0.83)	(0.84)	(0.88)								
Diesel		0.044	-0.108	0.029	0.048	0							
		(0.36)	(0.37)	(0.37)	(0.4)								
AFV		0.883**	0.325	0.262	0.834**	0							
		(0.38)	(0.39)	(0.4)	(0.41)								
Personal norms		0.077	0.014	0.031	0.072	0							
		(0.06)	(0.06)	(0.06)	(0.07)								
Technophilia		-0.074	-0.06	-0.014	-0.037	0							
		(0.05)	(0.06)	(0.06)	(0.06)								
Multicar		-0.222	0.261	0.186	-0.099	0							
		(0.37)	(0.37)	(0.38)	(0.41)								
Social group		-0.46	-2.493***	-2.102***	-1.063**	0							
		(0.43)	(0.65)	(0.59)	(0.52)								
Constant		0.3	1.036	0.753	-0.788	0							
		(0.69)	(0.7)	(0.73)	(0.79)								
Class probabilities		0.12	0.21	0.22	0.21	0.23							
LL	-8,843.1	-6,920.4											
df	14	122											
AIC	17,714.2	14,084.7											
BIC	17,829.4	15,088.2											
N	27,584	27,584											
N respondents	862	862											

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients at 10%
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Chapter 6

Conclusion

In this thesis data from a discrete choice experiment, where respondents chose between 4 alternatives of passenger vehicles — conventional (CVs), hybrid electric (HEVs), plug-in hybrid electric (PHEVs), and battery electric ones (BEVs) — characterised by varying levels of attributes, were analysed. In order to analyse preferences, conditional logit model was applied first. Specification tests, however, rejected the hypothesis that the inherent property of this model, the Independence of Irrelevant Alternatives (IIA), would hold.

Taking this finding into account, models which allow to relax this restrictive IIA assumption — the mixed logit and latent class models — were utilized. Results of the mixed logit show that on average respondents oppose adopting electricity-driven vehicles (EVs) and prefer to keep using conventional vehicles. High standard deviations of attributes parameters assumed to be normally distributed within the mixed logit specification, however, point towards high heterogeneity of preferences for these technologies, indicating presence of respondents in the population who would actually favour electric vehicles.

Comparing mixed logit with latent class models with varying number of classes using the Akaike's (AIC) and Schwarz's Bayesian (BIC) information criteria, suggests that latent class model statistically outperforms the mixed logit one. Moreover, the use of latent class model allows to distinguish distinct segments in the population, among which preferences for different types of passenger vehicles significantly differ. Models assuming 3 and 5 latent classes were selected, as they allowed for the best interpretation and identification of preference classes.

When assuming 3 latent classes, the population was clearly divided into those with strong opposition to EVs, those preferring both hybrid types of vehicles, and those in favour of battery electric cars. The probabilities of belonging to the EV-preference classes were not negligible. In fact the division of respondents into different preference segments was rather even.

Compared to the group with strong preferences for conventional vehicles, those in hybrid vehicles preferring group were found to favour new technologies more, are more likely to live in the city centres or in the suburbs, and are potentially richer. For those favouring battery electric vehicles possibility to park their car at a garage at home turned out to be more likely. Both groups preferring EVs were found more likely to already consider purchasing an alternative fuel vehicle (AFV), and their closest ones would also probably do so. This might propose importance of social networks when promoting greater adoption of EVs. There was, however, no evidence found that would suggest that owning more than one car would result in higher preferences for electric vehicles.

Assuming that there are 5 latent classes in the population, resulted in even subtler division of respondents into preference groups, again with almost even division between segments. The following groups were identified — a segment in strong opposition to any EV, a group still opposing any EV, but with weaker preferences for conventional vehicles, a group in favour of pure hybrid vehicles, a group preferring plug-in hybrid vehicles, and a segment with preferences for battery electric vehicles.

Respondents belonging to hybrid car preferring groups are again found to favour new technologies, and are more likely to be living in the city centres or in the suburbs. Those favouring plug-in technologies (plug-in hybrids and battery electric vehicles) turned out more likely than those with strong preferences for conventional vehicles to have the possibility to park their car in a garage at home. Using model with 5 latent classes actually confirmed the hypothesis that respondents owning more than one car would prefer battery electric vehicles. All preferring an EV are again found to be surrounded by people already considering buying an AFV.

Even though the results show that on average it would require a compensation around 22,200zł (€5,311) [6] for an average respondent to switch from using a conventional vehicle to using a pure hybrid one, about one quarter of the respondents would in fact be willing to pay around 10,100zł (€2,417) for this change holding all attributes constant. For plug-in hybrid vehicles the average compensation would have to be around 16,100zł (€3,875), although around

[6] The exchange rate used in the average exchange rate for the year 2014 — €1 = 4.18zł

one fifth of the respondents would be willing to pay about 21,400zł (€5,128) to change to using plug-in hybrids. For the battery electric vehicles the average compensation required resulted to be around 18,200zł (€4,360), while around one quarter of respondents would be willing to pay around 92,800zł (€22,199) for the switch to battery electric vehicles from conventional ones holding everything else constant.

The analysis was conducted on two independent samples — one stating clear intention to buy a passenger vehicle with equal proportion of those intending to buy a used vehicle, and those planning to buy a new one or are still undecided (Sample A), and the other one representing a general Polish population with intention to buy a passenger vehicle (Sample B). The qualitative results turned out not to differ between the two samples.

Respondents planning to buy a brand new passenger vehicle were, however, found to oppose any electricity-driven vehicle much more than those intending to purchase a used one. They would have to be given a compensation of around 40,000zł (€9,569) for the switch to hybrid electric vehicles, about 45,500zł (€10,901) to switch to using plug-in hybrid electric, and around 50,500zł (€12,071) for the switch to battery electric cars. This might be caused by the fact that new car buyers are much less sensitive to the change in purchase price. Despite this overall opposition to electricity-driven vehicles, latent class model with 3 latent classes shows that as much as 40% of new car buyers from Sample A would be willing to pay around 9,800zł (€2,339) to switch to pure hybrid vehicles and about 20,500zł (€4,897) to change to using plug-in hybrid electric vehicles, while 32% of those intending to buy a new car would be willing to pay around 65,000zł (€15,559) for the switch to battery electric vehicles.

As for the future work, it might be interesting to see how preferences change within individual classes using the combination of latent class and mixed logit models, which assume class parameters to follow a prespecified distribution. In addition, looking at how the unconditional probabilities of choosing an individual technology would change when changing the relevant attributes, or simulating market shares under different scenarios might help in understanding the demand for electricity-driven vehicles better.

Bibliography

Achtnicht, M. (2012): "German car buyers' willingness to pay to reduce CO2 emissions." *Climatic change* **113(3-4)**: pp. 679–697.

Achtnicht, M., G. Bühler, & C. Hermeling (2012): "The impact of fuel availability on demand for alternative-fuel vehicles." *Transportation Research Part D: Transport and Environment* **17(3)**: pp. 262–269.

Akaike, H. (1974): "A new look at the statistical model identification." *IEEE transactions on automatic control* **19(6)**: pp. 716–723.

Axsen, J., J. Bailey, & M. A. Castro (2015): "Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers." *Energy Economics* **50**: pp. 190–201.

Axsen, J., D. C. Mountain, & M. Jaccard (2009): "Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles." *Resource and Energy Economics* **31(3)**: pp. 221–238.

Bahamonde-Birke, F. J. & T. Hanappi (2016): "The potential of electromobility in austria: Evidence from hybrid choice models under the presence of unreported information." *Transportation Research Part A: Policy and Practice* **83**: pp. 30–41.

Batley, R., J. Toner, & M. Knight (2004): "A mixed logit model of uk household demand for alternative-fuel vehicles." *International Journal of Transport Economics/Rivista internazionale di economia dei trasporti* pp. 55–77.

Beggs, S., S. Cardell, & J. Hausman (1981): "Assessing the potential demand for electric cars." *Journal of econometrics* **17(1)**: pp. 1–19.

Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, D. Bolduc, A. Boersch-Supan, D. Brownstone, D. S. Bunch *et al.* (2002): "Hybrid choice models: progress and challenges." *Marketing Letters* **13(3)**: pp. 163–175.

Bliemer, M. C., J. M. Rose, & S. Hess (2008): "Approximation of bayesian efficiency in experimental choice designs." *Journal of Choice Modelling* **1(1)**: pp. 98–126.

Bočkarjova, M., P. Rietveld, & J. Knockaert (2013): "Adoption of electric vehicle in the netherlands-a stated choice experiment." .

Boxall, P. C. & W. L. Adamowicz (2002): "Understanding heterogeneous preferences in random utility models: a latent class approach." *Environmental and resource economics* **23(4)**: pp. 421–446.

Bozdogan, H. (1987): "Model selection and akaike's information criterion (aic): The general theory and its analytical extensions." *Psychometrika* **52(3)**: pp. 345–370.

Brownstone, D., D. S. Bunch, & K. Train (2000): "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles." *Transportation Research Part B: Methodological* **34(5)**: pp. 315–338.

Brownstone, D. & K. Train (1998): "Forecasting new product penetration with flexible substitution patterns." *Journal of econometrics* **89(1)**: pp. 109–129.

Bunch, D. S., M. Bradley, T. F. Golob, R. Kitamura, & G. P. Occhiuzzo (1993): "Demand for clean-fuel vehicles in california: a discrete-choice stated preference pilot project." *Transportation Research Part A: Policy and Practice* **27(3)**: pp. 237–253.

Cartenì, A., E. Cascetta, & S. de Luca (2016): "A random utility model for park & carsharing services and the pure preference for electric vehicles." *Transport Policy* **48**: pp. 49–59.

Caulfield, B., S. Farrell, & B. McMahon (2010): "Examining individuals preferences for hybrid electric and alternatively fuelled vehicles." *Transport Policy* **17(6)**: pp. 381–387.

Chipman, J. S. (1960): "The foundations of utility." *Econometrica: Journal of the Econometric Society* pp. 193–224.

Chorus, C. G., M. J. Koetse, & A. Hoen (2013): "Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model." *Energy policy* **61**: pp. 901–908.

Dagsvik, J. K. & G. Liu (2009): "A framework for analyzing rank-ordered data with application to automobile demand." *Transportation Research Part A: Policy and Practice* **43(1)**: pp. 1–12.

Dagsvik, J. K., T. Wennemo, D. G. Wetterwald, & R. Aaberge (2002): "Potential demand for alternative fuel vehicles." *Transportation Research Part B: Methodological* **36(4)**: pp. 361–384.

Daziano, R. A. (2013): "Conditional-logit bayes estimators for consumer valuation of electric vehicle driving range." *Resource and Energy Economics* **35(3)**: pp. 429–450.

Daziano, R. A. & D. Bolduc (2013): "Incorporating pro-environmental preferences towards green automobile technologies through a bayesian hybrid choice model." *Transportmetrica A: Transport Science* **9(1)**: pp. 74–106.

Dumortier, J., S. Siddiki, S. Carley, J. Cisney, R. M. Krause, B. W. Lane, J. A. Rupp, & J. D. Graham (2015): "Effects of providing total cost of ownership information on consumersâ€™ intent to purchase a hybrid or plug-in electric vehicle." *Transportation Research Part A: Policy and Practice* **72**: pp. 71–86.

Erdem, C., İ. Şentürk, & T. Şimşek (2010): "Identifying the factors affecting the willingness to pay for fuel-efficient vehicles in turkey: a case of hybrids." *Energy Policy* **38(6)**: pp. 3038–3043.

Ewing, G. & E. Sarigöllü (2000): "Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment." *Journal of public policy & marketing* **19(1)**: pp. 106–118.

Ferrini, S. & R. Scarpa (2007): "Designs with a priori information for non-market valuation with choice experiments: A monte carlo study." *Journal of environmental economics and management* **53(3)**: pp. 342–363.

Glerum, A., L. Stankovikj, M. Thémans, & M. Bierlaire (2013): "Forecasting the demand for electric vehicles: accounting for attitudes and perceptions." *Transportation Science* **48(4)**: pp. 483–499.

Golob, T. F., J. Torous, M. Bradley, D. Brownstone, S. S. Crane, & D. S. Bunch (1997): "Commercial fleet demand for alternative-fuel vehicles in california." *Transportation Research Part A: Policy and Practice* **31(3)**: pp. 219–233.

Greene, W. H. & D. A. Hensher (2003): "A latent class model for discrete choice analysis: contrasts with mixed logit." *Transportation Research Part B: Methodological* **37(8)**: pp. 681–698.

Haab, T. C. & K. E. McConnell (2002): *Valuing environmental and natural resources: the econometrics of non-market valuation.* Edward Elgar Publishing.

Hackbarth, A. & R. Madlener (2013): "Consumer preferences for alternative fuel vehicles: A discrete choice analysis." *Transportation Research Part D: Transport and Environment* **25**: pp. 5–17.

Hackbarth, A. & R. Madlener (2016): "Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for germany." *Transportation Research Part A: Policy and Practice* **85**: pp. 89–111.

Hanley, N., S. Mourato, & R. E. Wright (2001): "Choice modelling approaches: a superior alternative for environmental valuatioin?" *Journal of economic surveys* **15(3)**: pp. 435–462.

Hausman, J. & D. McFadden (1984): "Specification tests for the multinomial logit model." *Econometrica: Journal of the Econometric Society* pp. 1219–1240.

Helveston, J. P., Y. Liu, E. M. Feit, E. Fuchs, E. Klampfl, & J. J. Michalek (2015): "Will subsidies drive electric vehicle adoption? measuring consumer preferences in the us and china." *Transportation Research Part A: Policy and Practice* **73**: pp. 96–112.

Hess, S., M. Ben-Akiva, D. Gopinath, & J. Walker (2011): "Advantages of latent class over continuous mixture of logit models." *Institute for Transport Studies, University of Leeds. Working paper* .

Hess, S., M. Fowler, T. Adler, & A. Bahreinian (2012): "A joint model for vehicle type and fuel type choice: evidence from a cross-nested logit study." *Transportation* **39(3)**: pp. 593–625.

Hidrue, M. K., G. R. Parsons, W. Kempton, & M. P. Gardner (2011): "Willingness to pay for electric vehicles and their attributes." *Resource and Energy Economics* **33(3)**: pp. 686–705.

Hoen, A. & M. J. Koetse (2014): "A choice experiment on alternative fuel vehicle preferences of private car owners in the netherlands." *Transportation Research Part A: Policy and Practice* **61**: pp. 199–215.

Horne, M., M. Jaccard, & K. Tiedemann (2005): "Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions." *Energy Economics* **27(1)**: pp. 59–77.

Ito, N., K. Takeuchi, & S. Managi (2013): "Willingness-to-pay for infrastructure investments for alternative fuel vehicles." *Transportation Research Part D: Transport and Environment* **18**: pp. 1–8.

Jensen, A. F., E. Cherchi, & S. L. Mabit (2013): "On the stability of preferences and attitudes before and after experiencing an electric vehicle." *Transportation Research Part D: Transport and Environment* **25**: pp. 24–32.

Kim, J., S. Rasouli, & H. Timmermans (2014): "Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars." *Transportation research part A: policy and practice* **69**: pp. 71–85.

Kochhan, R. & M. Hörner (2015): "Costs and willingness-to-pay for electric vehicles." In "Sustainable Automotive Technologies 2014," pp. 13–21. Springer.

Koetse, M. J. & A. Hoen (2014): "Preferences for alternative fuel vehicles of company car drivers." *Resource and Energy Economics* **37**: pp. 279–301.

Kurani, K. S., T. Turrentine, & D. Sperling (1996): "Testing electric vehicle demand in 'hybrid households' using a reflexive survey." *Transportation Research Part D: Transport and Environment* **1(2)**: pp. 131–150.

Lancaster, K. J. (1966): "A new approach to consumer theory." *Journal of political economy* **74(2)**: pp. 132–157.

Lebeau, K., J. Van Mierlo, P. Lebeau, O. Mairesse, & C. Macharis (2012): "The market potential for plug-in hybrid and battery electric vehicles in flanders: A choice-based conjoint analysis." *Transportation Research Part D: Transport and Environment* **17(8)**: pp. 592–597.

Link, C., U. Raich, G. Sammer, & J. Stark (2012): "Modeling demand for electric cars-a methodical approach." *Procedia-Social and Behavioral Sciences* **48**: pp. 1958–1970.

Louviere, J. J., D. A. Hensher, & J. D. Swait (2000): *Stated choice methods: analysis and applications.* Cambridge University Press.

Luce, R. D. (1959): *Individual Choice Behavior: A Theoretical analysis.* New York, NY, USA: John Wiley & Sons.

Mabit, S. L., E. Cherchi, A. F. Jensen, & J. Jordal-Jørgensen (2015): "The effect of attitudes on reference-dependent preferences: Estimation and validation for the case of alternative-fuel vehicles." *Transportation Research Part A: Policy and Practice* **82**: pp. 17–28.

Mabit, S. L. & M. Fosgerau (2011): "Demand for alternative-fuel vehicles when registration taxes are high." *Transportation Research Part D: Transport and Environment* **16(3)**: pp. 225–231.

Mau, P., J. Eyzaguirre, M. Jaccard, C. Collins-Dodd, & K. Tiedemann (2008): "The 'neighbor effect': Simulating dynamics in consumer preferences for new vehicle technologies." *Ecological Economics* **68(1)**: pp. 504–516.

McFadden, D. (1973): "Conditional logit analysis of qualitative choice behaviour." In P. Zarembka (editor), "Frontiers in Econometrics," pp. 105–142. New York, NY, USA: Academic Press New York.

McFadden, D. (1987): "Regression-based specification tests for the multinomial logit model." *Journal of econometrics* **34(1-2)**: pp. 63–82.

McFadden, D. & K. Train (2000): "Mixed mnl models for discrete response." *Journal of applied Econometrics* pp. 447–470.

Parsons, G. R., M. K. Hidrue, W. Kempton, & M. P. Gardner (2014): "Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms." *Energy Economics* **42**: pp. 313–324.

Potoglou, D. & P. S. Kanaroglou (2007): "Household demand and willingness to pay for clean vehicles." *Transportation Research Part D: Transport and Environment* **12(4)**: pp. 264–274.

Qian, L. & D. Soopramanien (2011): "Heterogeneous consumer preferences for alternative fuel cars in china." *Transportation Research Part D: Transport and Environment* **16(8)**: pp. 607–613.

Rasouli, S. & H. Timmermans (2016): "Influence of social networks on latent choice of electric cars: a mixed logit specification using experimental design data." *Networks and Spatial Economics* **16(1)**: pp. 99–130.

Rogers, E. M. (2003): "Elements of diffusion." *Diffusion of innovations* **5**: pp. 1–38.

Rose, J. M., M. C. Bliemer, D. A. Hensher, & A. T. Collins (2008): "Designing efficient stated choice experiments in the presence of reference alternatives." *Transportation Research Part B: Methodological* **42(4)**: pp. 395–406.

Rudolph, C. (2016): "How may incentives for electric cars affect purchase decisions?" *Transport Policy* **52**: pp. 113–120.

Sagebiel, J. (2011): "Comparing the latent class model with the random parameters logit. a choice experiment analysis of highly heterogeneous electricity consumers in hyderabad, india." In "II International Choice Modeling Conference, Leeds," .

Schwarz, G. *et al.* (1978): "Estimating the dimension of a model." *The annals of statistics* **6(2)**: pp. 461–464.

Sheldon, T. L., J. DeShazo, & R. T. Carson (2017): "Electric and plug-in hybrid vehicle demand: Lessons for an emerging market." *Economic Inquiry* **55(2)**: pp. 695–713.

Shin, J., C. R. Bhat, D. You, V. M. Garikapati, & R. M. Pendyala (2015): "Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types." *Transportation Research Part C: Emerging Technologies* **60**: pp. 511–524.

Shin, J., J. Hong, G. Jeong, & J. Lee (2012): "Impact of electric vehicles on existing car usage: A mixed multiple discrete–continuous extreme value model approach." *Transportation Research Part D: Transport and Environment* **17(2)**: pp. 138–144.

Stix, S. & T. Hanappi (2013): "Consumer demand for alternative-fuel vehicles and its impact on environmental goals." .

Swait, J. (2007): *Advanced Choice Models*, pp. 229–293. Dordrecht: Springer Netherlands.

Tanaka, M., T. Ida, K. Murakami, & L. Friedman (2014): "Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the us and japan." *Transportation Research Part A: Policy and Practice* **70**: pp. 194–209.

Train, K. (2003): *Discrete choice methods with simulation.* Cambridge university press.

Train, K. E. (2008): "Em algorithms for nonparametric estimation of mixing distributions." *Journal of Choice Modelling* **1(1)**: pp. 40–69.

Valeri, E. & E. Cherchi (2016): "Does habitual behavior affect the choice of alternative fuel vehicles?" *International Journal of Sustainable Transportation* **10(9)**: pp. 825–835.

Valeri, E. & R. Danielis (2015): "Simulating the market penetration of cars with alternative fuelpowertrain technologies in italy." *Transport Policy* **37**: pp. 44–56.

Ščasný, M., I. Zvěřinová, & M. Czajkowski (2015): "Individual preference for the alternative fuel vehicles and their attributes in Poland." .

Ziegler, A. (2012): "Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for germany." *Transportation Research Part A: Policy and Practice* **46(8)**: pp. 1372–1385.

Appendix A

Conditional and mixed logit models

Preliminary results using the conditional logit and both mixed logit (with and without correlated random parameters) models for samples A and B can be found in the following tables.

Table A.1: Conditional and mixed logit models using Sample A data

	CL	MXL uncorr		MXL corr	
		Mean	SD	Mean	SD
Purchase price	-0.369***	-0.556***		-0.552***	
(in 10,000 zł)	(0.03)	(0.02)		(0.02)	
Operational costs	-0.836***	-2.715***	2.08***	-2.504***	0.026
(in 100zł/100km)	(0.14)	(0.19)	(0.19)	(0.2)	(0.32)
Driving range	0.093***	0.122***	0.01	0.141***	0.036**
(in 100km)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Refuelling/recharging time	-0.04***	-0.124***	-0.311***	-0.069***	0.069**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Fast-mode recharging 2	0.282***	0.431***	0.209**	0.451***	0.613***
	(0.04)	(0.05)	(0.1)	(0.06)	(0.1)
Fast-mode recharging 3	0.486***	0.739***	0.479***	0.812***	0.857***
	(0.04)	(0.05)	(0.09)	(0.06)	(0.09)
Free parking	0.146***	0.185***	-0.392***	0.205***	0.261***
	(0.02)	(0.03)	(0.07)	(0.04)	(0.06)
Free public transport	0.099***	0.077**	0.564***	0.108**	0.346***
	(0.02)	(0.03)	(0.06)	(0.04)	(0.05)
HEV	-0.891***	-1.129***	1.549***	-0.762***	2.628***
	(0.05)	(0.06)	(0.06)	(0.08)	(0.09)
PHEV	-0.667***	-0.913***	1.485***	-0.567***	2.736***
	(0.05)	(0.07)	(0.06)	(0.09)	(0.11)
BEV	-0.456***	-1.606***	-2.03***	-1.338***	3.556***
	(0.09)	(0.12)	(0.08)	(0.16)	(0.15)
LL	-17,185.4	-14,213.1		-13,302.5	
df	11	21		66	
AIC	34,392.8	28,468.3		26,737.0	
BIC	34,490.5	28,654.8		27,323.2	
N	53,248	53,248		53,248	
N respondents	1,664	1,664		1,664	

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

The sign of the estimated standard deviations is irrelevant and should be interpreted as positive.

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Table A.2: Conditional and mixed logit models using Sample B data

	CL	MXL uncorr		MXL corr	
		Mean	SD	Mean	SD
Purchase price	-0.429***	-0.62***		-0.623***	
(in 10,000 zł)	(0.07)	(0.04)		(0.43)	
Operational costs	-0.758**	-2.298***	2.293***	-1.929***	0.665
(in 100zł/100km)	(0.26)	(0.37)	(0.32)	(0.33)	(0.44)
Driving range	0.094***	0.107***	0.089**	0.138***	0.128***
(in 100km)	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)
Refuelling/recharging time	-0.029*	-0.14***	0.441***	-0.043*	0.102**
	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)
Fast-mode recharging 2	0.376***	0.464***	0.213	0.553***	0.441**
	(0.07)	(0.1)	(0.17)	(0.11)	(0.18)
Fast-mode recharging 3	0.419***	0.591***	0.356*	0.661***	0.788***
	(0.07)	(0.09)	(0.21)	(0.11)	(0.15)
Free parking	0.177***	0.197**	0.519***	0.222***	0.53***
	(0.04)	(0.06)	(0.13)	(0.07)	(0.09)
Free public transport	0.092**	0.051	0.473***	0.109*	0.385***
	(0.04)	(0.06)	(0.12)	(0.07)	(0.09)
HEV	-0.885***	-1.172***	1.699***	-0.537**	3.175***
	(0.1)	(0.12)	(0.11)	(0.18)	(0.2)
PHEV	-0.726***	-0.813***	1.47***	-0.365**	3.03***
	(0.1)	(0.12)	(0.1)	(0.18)	(0.21)
BEV	-0.491**	-1.404***	1.627***	-0.997***	3.65***
	(0.18)	(0.23)	(0.18)	(0.28)	(0.28)
LL	-4,949.4	-4,044.9		-3,742.7	
df	11	21		66	
AIC	9,920.7	8,131.9		7,617.3	
BIC	10,004.7	8,292.2		8,121.2	
N	15,296	15,296		15,296	
N respondents	478	478		478	

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

The sign of the estimated standard deviations is irrelevant and should be interpreted as positive.

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Appendix B

Models with 2 latent classes

Models assuming 2 latent classes using all data from Sample A and Sample B as well as data on new and used car buyers from Sample A will be presented in this Appendix.

Table B.1: Models with 2 latent classes using all data

	Sample A - all data					Sample B - all data				
	Parameters		WTP			Parameters		WTP		
	Class 1	Class 2	Class 1	Class 2	Weighted average	Class 1	Class 2	Class 1	Class 2	Weighted average
Class-specific parameters										
Purchase price	-0.377***	-0.503***				-0.414***	-0.613***			
(in 10,000zł)	(0.02)	(0.05)				(0.03)	(0.11)			
Operational costs	-0.896***	-1.387***	-2.3782	-2.7567	-2.4997	-0.831***	-1.049*	-2.0065	-1.7101	-1.9019
(in 100zł/100km)	(0.1)	(0.31)	(0.27)	(0.645)	(0.39)	(0.17)	(0.6)	(0.439)	(1.009)	(0.64)
Driving range	0.114***	0.121***	0.3016	0.2414	0.2822	0.122***	0.093**	0.2942	0.1516	0.2439
(in 100km)	(0.01)	(0.02)	(0.025)	(0.041)	(0.03)	(0.02)	(0.03)	(0.044)	(0.054)	(0.048)
Refuelling/recharging time	0.001	0.068	0.0029b	0.1347b	0.0452	-0.023	-0.084*	-0.0561b	-0.1362	-0.0844
	(0.02)	(0.05)	(0.063)	(0.108)	(0.077)	(0.02)	(0.05)	(0.04)	(0.079)	(0.054)
Refuelling/recharging time x BEV	-0.066**	-0.159**	-0.1741	-0.3154	-0.2195					
	(0.03)	(0.07)	(0.079)	(0.142)	(0.099)					
Fast-mode recharging 2	0.297***	0.253	0.7895	0.5021b	0.6973	0.401***	0.294	0.9691	0.4793b	0.7962
	(0.06)	(0.17)	(0.165)	(0.334)	(0.22)	(0.08)	(0.2)	(0.201)	(0.335)	(0.248)
Fast-mode recharging 3	0.442***	0.599***	1.1744	1.1907	1.1796	0.457***	0.454**	1.104	0.7401	0.9755
	(0.06)	(0.15)	(0.162)	(0.32)	(0.213)	(0.08)	(0.2)	(0.198)	(0.34)	(0.248)
Fast-mode recharging 2 x BEV	0.05	0.312	0.1318b	0.6197b	0.2884					
	(0.09)	(0.31)	(0.227)	(0.613)	(0.351)					
Fast-mode recharging 3 x BEV	0.115	0.539*	0.3064b	1.0707	0.5517					
	(0.08)	(0.28)	(0.22)	(0.569)	(0.332)					
Free parking	0.15***	0.23**	0.3989	0.4563	0.4173	0.193***	0.125	0.4666	0.2044b	0.3741
	(0.02)	(0.08)	(0.067)	(0.166)	(0.099)	(0.05)	(0.13)	(0.115)	(0.221)	(0.153)
Free public transport	0.117***	0.109	0.3106	0.2166b	0.2804	0.055	0.346**	0.1316b	0.5635	0.2841
	(0.03)	(0.08)	(0.07)	(0.163)	(0.1)	(0.05)	(0.14)	(0.112)	(0.247)	(0.159)
HEV	0.277***	-2.728***	0.7348	-5.4217	-1.2415	0.541***	-2.919***	1.3075	-4.7589	-0.8339
	(0.05)	(0.12)	(0.135)	(0.591)	(0.281)	(0.11)	(0.2)	(0.28)	(0.943)	(0.514)
PHEV	0.448***	-2.725***	1.1901	-5.4166	-0.9307	0.629***	-2.398***	1.5178	-3.9094	-0.398
	(0.07)	(0.18)	(0.196)	(0.661)	(0.345)	(0.12)	(0.21)	(0.315)	(0.778)	(0.478)
BEV	0.906***	-3.512***	2.4059	-6.9809	-0.6072	1.002***	-2.721***	2.4202	-4.4358	0.0001
	(0.09)	(0.32)	(0.272)	(0.875)	(0.466)	(0.17)	(0.4)	(0.46)	(1.022)	(0.658)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients
* Significant at 10%
** Significant at 5%
*** Significant at 1%

(Continued)

Table B.1: Continued

	Sample A - all data					Sample B - all data				
	Parameters		WTP			Parameters		WTP		
	Class 1	Class 2	Class 1	Class 2	Weighted average	Class 1	Class 2	Class 1	Class 2	Weighted average
Class assignment parameters										
City center	-0.157	0				0.809**	0			
	(0.17)					(0.33)				
Suburbs	-0.048	0				0.395	0			
	(0.15)					(0.29)				
Family house	0.119	0				-0.353	0			
	(0.15)					(0.29)				
Garage at home	-0.024	0				0.516**	0			
	(0.13)					(0.25)				
Missing income	0.319	0				-0.85*	0			
	(0.24)					(0.46)				
Household income	0.267	0				-0.508	0			
	(0.2)					(0.46)				
Diesel	0.091	0				0.054	0			
	(0.12)					(0.23)				
AFV	0.559***	0				0.537**	0			
	(0.12)					(0.23)				
Personal norms	0.037*	0				0.047	0			
	(0.02)					(0.04)				
Technophilia	0.008	0				0.073*	0			
	(0.02)					(0.04)				
Multicar	-0.314**	0				0.11	0			
	(0.12)					(0.25)				
Social group	1.402***	0				1.596**	0			
	(0.28)					(0.55)				
Constant	0.14	0				-1.087**	0			
	(0.23)					(0.52)				
Class probabilities	0.68	0.32				0.65	0.35			
LL	-15,035					-4,277				
df	41					35				
AIC	30,151.4					8,624.3				
BIC	30,515.6					8,891.5				
N	53,248					15,264				
N respondents	1,664					477				

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients

* Significant at 10%

** Significant at 5%

*** Significant at 1%

Table B.2: Models with 2 latent classes using data on new and used car buyers

	Sample A - new car buyers					Sample A - used car buyers				
	Parameters		WTP			Parameters		WTP		
	Class 1	Class 2	Class 1	Class 2	Weighted average	Class 1	Class 2	Class 1	Class 2	Weighted average
Class-specific parameters										
Purchase price	-0.37***	-0.262***				-0.495***	-0.66***			
(in 10,000 zł)	(0.07)	(0.02)				(0.11)	(0.04)			
Operational costs	-2.378***	-1.257***	-6.4185	-4.8014	-5.3787	-0.704*	-0.751***	-1.4238	-1.1366	-1.2331
(in 100zł/100km)	(0.72)	(0.28)	(2.143)	(1.099)	(1.472)	(0.38)	(0.12)	(0.787)	(0.195)	(0.394)
Driving range	0.125***	0.101***	0.3378	0.3865	0.3691	0.133***	0.124***	0.2681	0.187	0.2143
(in 100km)	(0.03)	(0.02)	(0.102)	(0.071)	(0.082)	(0.02)	(0.01)	(0.074)	(0.021)	(0.039)
Refuelling/recharging time	0.17	-0.083*	0.4597b	-0.3166	-0.0394	0.028	0.016	0.0568b	0.025b	0.0357
	(0.11)	(0.05)	(0.315)	(0.189)	(0.234)	(0.08)	(0.03)	(0.158)	(0.051)	(0.087)
Refuelling/recharging time x BEV	-0.073	0.023	-0.197b	0.0896b	-0.0127	-0.171*	-0.064	-0.3461	-0.0963b	-0.1802
	(0.13)	(0.06)	(0.365)	(0.237)	(0.283)	(0.09)	(0.04)	(0.211)	(0.063)	(0.113)
Fast-mode recharging 2	0.811**	0.107	2.1888	0.4084b	1.044	-0.087	0.376***	-0.1769b	0.5695	0.3187
	(0.31)	(0.13)	(0.938)	(0.482)	(0.645)	(0.24)	(0.09)	(0.485)	(0.136)	(0.253)
Fast-mode recharging 3	0.48	0.224*	1.2951b	0.8558	1.0126	0.493**	0.449***	0.9963	0.6794	0.7859
	(0.3)	(0.12)	(0.855)	(0.464)	(0.603)	(0.21)	(0.09)	(0.463)	(0.133)	(0.244)
Fast-mode recharging 2 x BEV	-1.411**	0.311*	-3.8078	1.1857	-0.597	0.923**	-0.002	1.8669	-0.0037b	0.6248
	(0.69)	(0.18)	(2.059)	(0.695)	(1.182)	(0.38)	(0.12)	(0.852)	(0.182)	(0.408)
Fast-mode recharging 3 x BEV	-0.342	0.423**	-0.9229b	1.6171	0.7103	0.8**	0.086	1.6184	0.1297b	0.6299
	(0.56)	(0.17)	(1.515)	(0.675)	(0.975)	(0.35)	(0.12)	(0.774)	(0.177)	(0.377)
Free parking	-0.13	0.178***	-0.3508b	0.681	0.3126	0.294**	0.142***	0.5955	0.2152	0.343
	(0.15)	(0.05)	(0.414)	(0.201)	(0.277)	(0.11)	(0.03)	(0.248)	(0.054)	(0.119)
Free public transport	-0.093	0.166**	-0.2501b	0.6335	0.318	0.262**	0.106**	0.5297	0.16	0.2843
	(0.16)	(0.05)	(0.442)	(0.211)	(0.294)	(0.11)	(0.04)	(0.255)	(0.056)	(0.123)
HEV	-2.228***	0.497***	-6.014	1.8991	-0.9259	-3.066***	0.237***	-6.1992	0.3587	-1.8448
	(0.19)	(0.12)	(1.178)	(0.47)	(0.723)	(0.17)	(0.07)	(1.408)	(0.106)	(0.544)
PHEV	-2.479***	0.97***	-6.6929	3.7039	-0.0077	-2.826***	0.342***	-5.7137	0.518	-1.5758
	(0.4)	(0.15)	(1.75)	(0.645)	(1.04)	(0.24)	(0.1)	(1.357)	(0.156)	(0.559)
BEV	-3.964***	0.768***	-10.7002	2.9312	-1.9352	-2.905***	0.964***	-5.8744	1.4599	-1.0044
	(0.64)	(0.21)	(2.505)	(0.826)	(1.426)	(0.37)	(0.13)	(1.382)	(0.22)	(0.61)

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places
b Indicates WTP values based on insignificant attribute coefficients
* Significant at 10%
** Significant at 5%
*** Significant at 1%

(Continued)

Table B.2: Continued

	Sample A - new car buyers					Sample A - used car buyers				
	Parameters		WTP			Parameters		WTP		
	Class 1	Class 2	Class 1	Class 2	Weighted average	Class 1	Class 2	Class 1	Class 2	Weighted average
Class assignment parameters										
City center	0.933** (0.37)	0				-0.05 (0.23)	0			
Suburbs	0.93** (0.33)	0				-0.285 (0.21)	0			
Family house	-0.112 (0.29)	0				-0.311 (0.21)	0			
Garage at home	0.09 (0.26)	0				0.047 (0.18)	0			
Missing income	0.185 (0.53)	0				-0.773** (0.36)	0			
Household income	-0.318 (0.33)	0				-0.282 (0.34)	0			
Diesel	-0.22 (0.26)	0				-0.161 (0.17)	0			
AFV	-0.643** (0.28)	0				-0.449** (0.17)	0			
Personal norms	-0.048 (0.04)	0				-0.051* (0.03)	0			
Technophilia	-0.008 (0.04)	0				0.008 (0.02)	0			
Multicar	0.231 (0.24)	0				0.421** (0.17)	0			
Social group	-1.246** (0.46)	0				-1.444*** (0.4)	0			
Constant	-0.511 (0.5)	0				0.119 (0.34)	0			
Class probabilities	0.36	0.64				0.34	0.66			
LL	-3,496.3					-7,735.0				
df	41					41				
AIC	7,074.5					15,551.9				
BIC	7,380.2					15,889.2				
N	12,768					27,584				
N respondents	399					862				

Notes: Fast-mode recharging 2 = at 60% of fuel stations and at half of public places; Fast-mode recharging 3 = at 90% of fuel stations and at almost all public places

b Indicates WTP values based on insignificant attribute coefficients

* Significant at 10%

** Significant at 5%

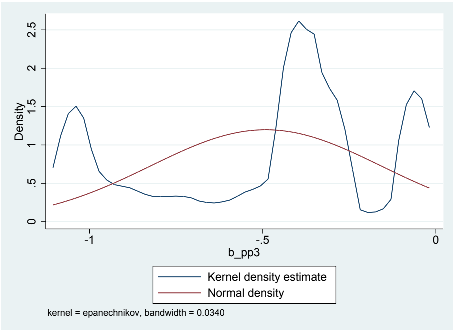
*** Significant at 1%

Appendix C

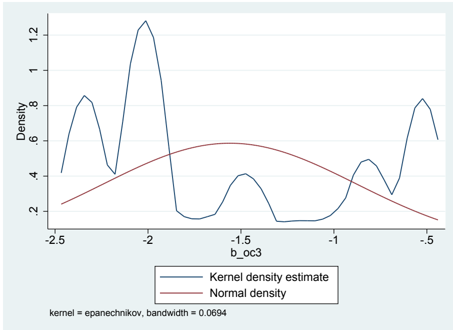
Individual-level densities

Densities of individual-level parameters for different attributes using all data from samples A and B can be found in the following.

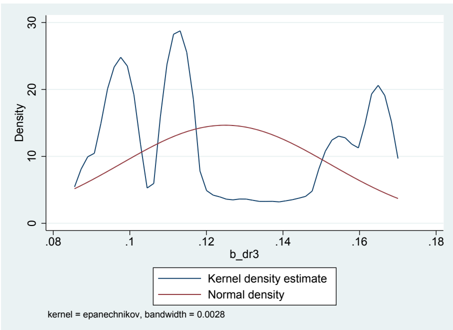
Figure C.1: Densities for attributes parameters - Sample A



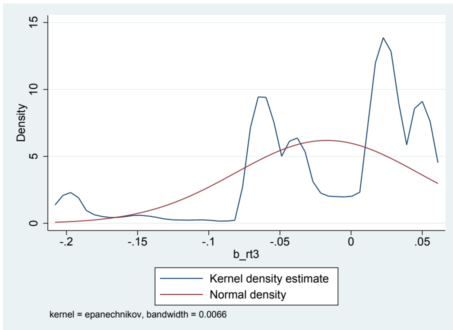
(a) Purchase price



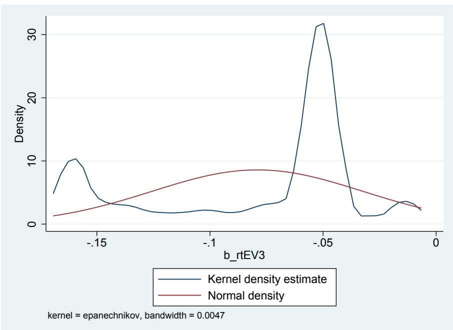
(b) Operational costs



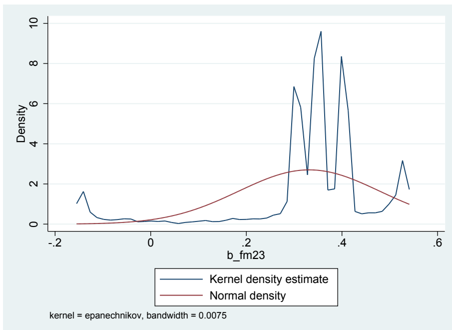
(c) Driving range



(d) Refuelling/recharging time

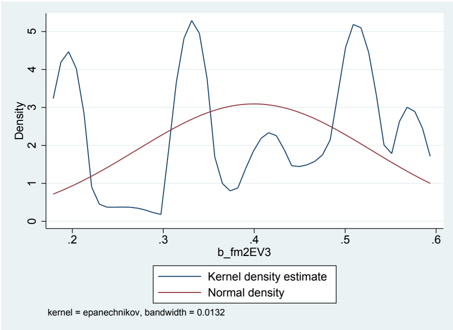


(e) Recharging time for BEVs

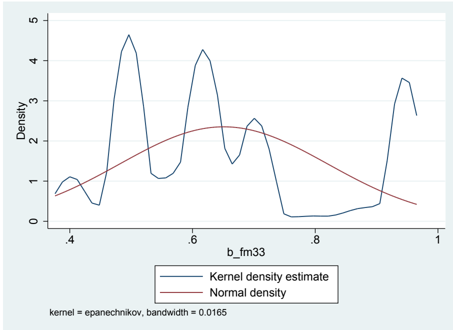


(f) Fast-mode recharging 2

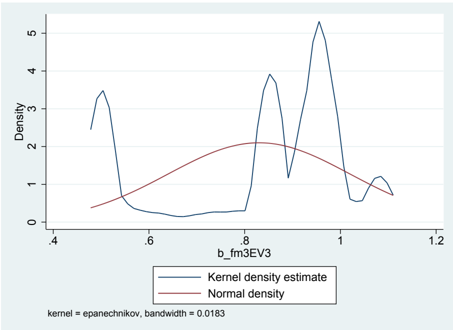
Figure C.1: Continued



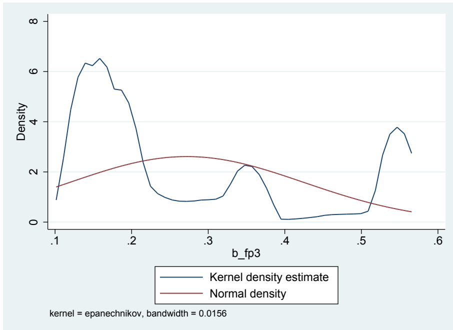
(g) Fast-mode recharging 2 for BEVs



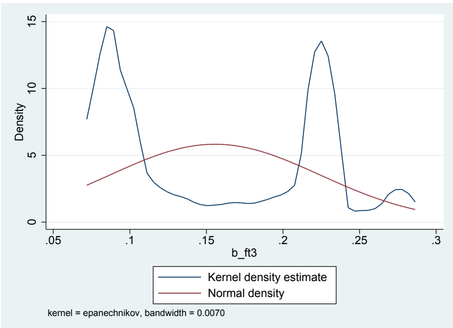
(h) Fast-mode recharging 3



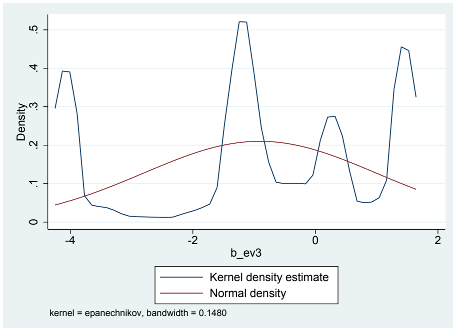
(i) Fast-mode recharging 3 for BEVs



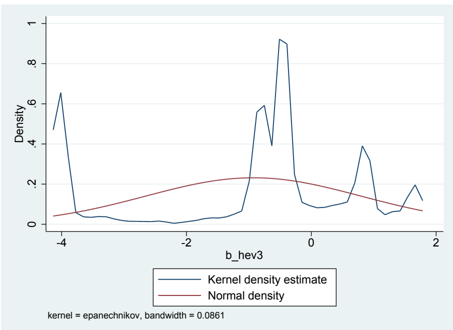
(j) Free parking



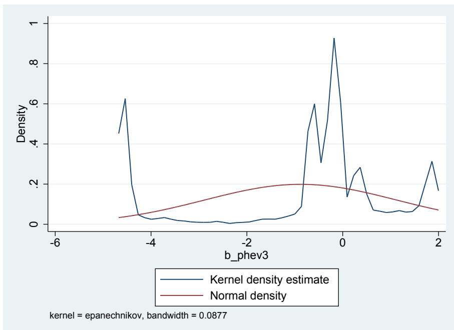
(k) Free public transport



(l) Battery electric vehicles

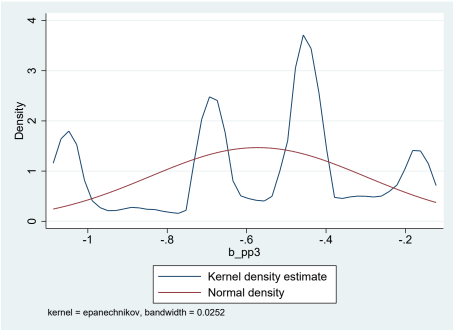


(m) Hybrid electric vehicles

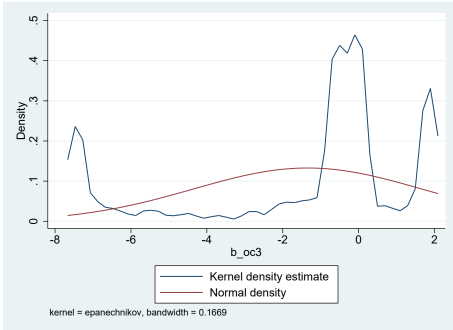


(n) Plug-in hybrid electric vehicles

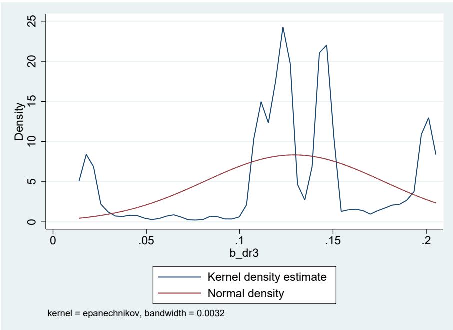
Figure C.2: Densities for attributes parameters - Sample B



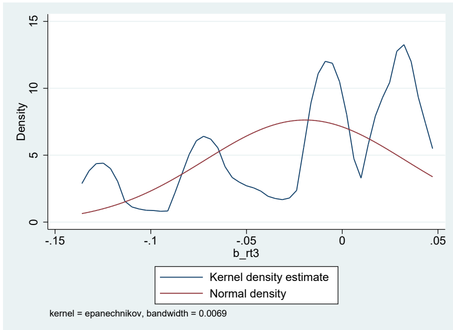
(a) Purchase price



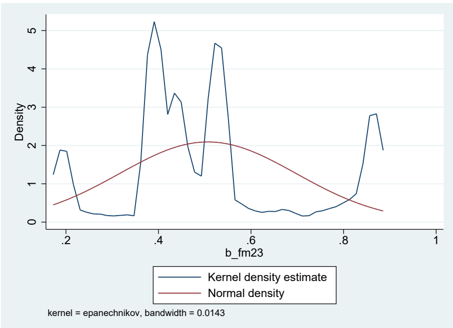
(b) Operational costs



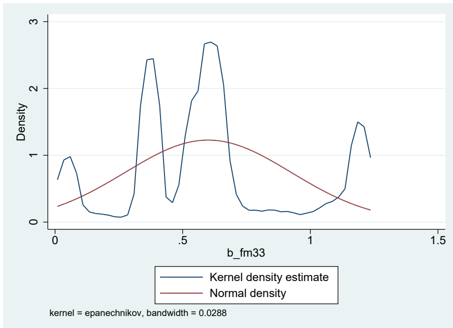
(c) Driving range



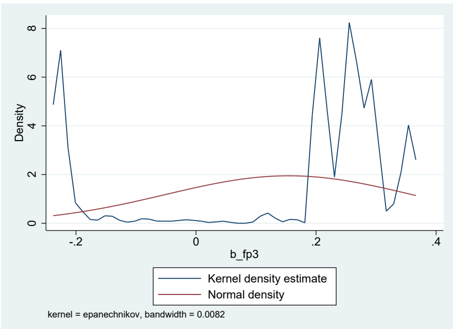
(d) Refuelling/recharging time



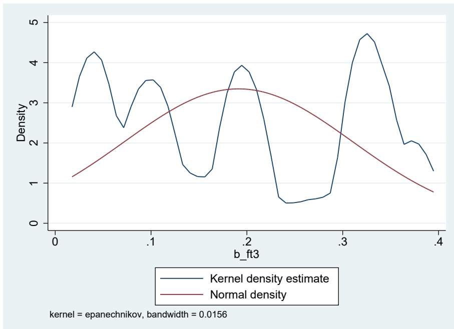
(e) Fast-mode recharging 2



(f) Fast-mode recharging 3

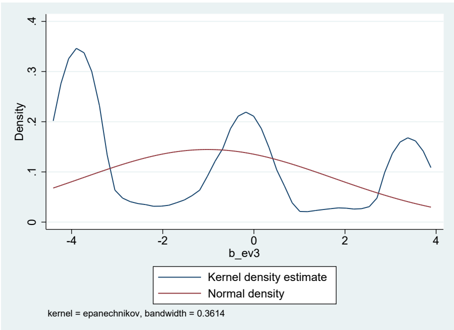


(g) Free parking

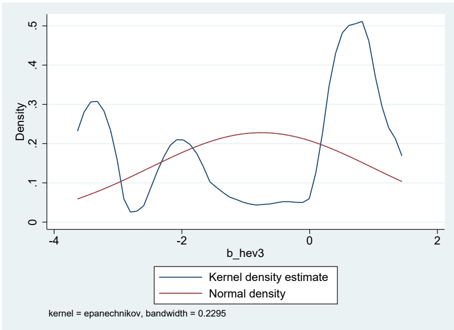


(h) Free public transport

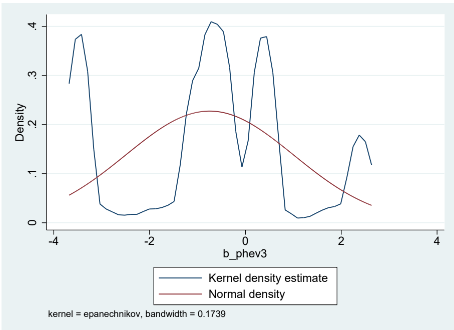
Figure C.2: Continued



(i) Battery electric vehicles



(j) Hybrid electric vehicles



(k) Plug-in hybrid electric vehicles