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Electric Vehicles, Business Models and Consumer Choices

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Electric Vehicles, Business Models and Consumer Choices

Dissertation

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For my grandpa and grandma

献给我的爷爷奶奶

Preface

Under the influence of my family members who work in universities, I have thought of obtaining a PhD degree as the default path in my life ever since I was little. Only after I really started my journey towards a PhD degree did I realize how this coincidental choice happened to offer a lifestyle which fits my preferences perfectly: the freedom of choosing your own research topic to focus on, the huge amount of time spent on reading literature in different fields, the requirement of delving into a specific topic instead of merely scratching the surface, the flexibility of working time and space, and so on.

Eric Molin, thank you for your supervision which already started since my master thesis period. Your gentleness made all our weekly meetings stress-free, your meticulousness enabled you to detect small flaws even in the last version of a manuscript which you have read many times, and your preference for clarity is the perfect balance force for my sometimes overly concise writing style. It is my pleasure to be the first PhD with you as promotor. Bert van Wee, thank you for always being so thoughtful, supportive and helpful. What amazed me the most are your seemingly endless stream of ideas and the capability to illustrate them and put them into context via clear conceptualizations. Harry Timmermans, thank you for your fast responses to emails and succinct and straight-to-the-point comments.

Yashar and Karimah, thank you for generating a warm atmosphere in the office when I just started. Maarten, thank you for checking one of my papers. Conchita, thank you for your help especially during the production process of the hard copy thesis. I would also like to thank all other TLO colleagues who helped me in different ways during my PhD research.

I would like to thank my mom and dad for their support all along.

Yeye and nainai, I feel extremely lucky and grateful that I grew up with you. The love and education you gave me is all a kid can ever wish for. Yeye, I am so sorry that I did not finish earlier and I hope this can make you smile.

Thomas, thank you for everything, especially the hot water and witty remarks.

Fanchao Liao

Changsha, April 2019

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1. Introduction

1.1 Background

Road transport currently is still heavily relying on fossil fuels: 94% of the energy demands are met by crude oil[1]. Consequently, it contributes to a series of problems including pollution, greenhouse gas emission, fuel dependence, etc. It accounts for about 20% of EU's total emissions of carbon dioxide and is the only major sector where the emission is still increasing[2]. It also remains a significant source for some of the most harmful pollutants in air[3].

Replacing fossil-fuel powered vehicles with electric vehicles (EV) on a large scale can serve as a potential solution to alleviate these problems, since EVs do not consume fossil fuels directly and electricity can be generated by renewable energy sources. Therefore, many countries including the Netherlands, France, Germany and UK have announced that they will issue a ban on sales of new fossil fuel cars by 2030/40 (Norway plans to commence starting from 2025)[4].

Since the majority of cars are light-duty passenger cars, governments have proposed or implemented policies which aim to increase EV penetration in the passenger car market, including incentives for EV purchase and development of public charging infrastructure. However, the market share of EVs remains low in the vast majority of countries despite the governmental promotion. Battery electric vehicles (BEVs) and Plug-In Hybrid Vehicles (PHEVs) together only account for 1.1% of worldwide car sales in 2016[5].

In order to achieve the goal of phasing out fossil fuel powered cars, it is of utmost importance to understand consumer preferences for EV which facilitates the development of more effective policy instruments. There has been a body of literature investigating the factors which affect EV adoption. The most prominent barriers identified include the high initial purchase price caused by the expensive batteries, the limited driving range, the rather long

[1] https://ec.europa.eu/transport/themes/urban/cpt_en
[2] https://ec.europa.eu/clima/policies/transport/vehicles_en
[3] https://www.eea.europa.eu/publications/explaining-road-transport-emissions
[4] https://en.wikipedia.org/wiki/List_of_countries_banning_fossil_fuel_vehicle
[5] https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf

charging time, the lagging behind of charging infrastructure development and the uncertainties surrounding battery lifetime and residue value (Chapter 2 will further elaborate on this topic). Most of these barriers are regarded inevitable given the current level of battery technology, therefore policy suggestions mainly focus on financing the R&D of battery technology which is certainly a fundamental way of increasing the competence of EV. However, an often-ignored notion is that the value of the technology itself is neither inherent nor fixed, and we can already attempt to boost the value of the technology and overcome some of the barriers in the meantime.

The value of technology depends on the way in which it is commercialized, which is usually termed as "business model". The two basic components of business models which are relevant to consumers are value proposition which is the product or service provided by the company; and the revenue model which means the way in which the company charges its customers (Kley, Lerch and Dallinger, 2011; Bohnsack, Pinkse and Kolk, 2014). Take the most common business model in car market for example: the value proposition is the full ownership of a car, and the revenue model is an upfront payment of the purchase price.

Apart from the dominant option of full purchase, there are several alternative business models available if consumers want to drive a car, including vehicle leasing and carsharing. In the case of vehicle leasing, consumers pay a monthly leasing rate and have exclusive access to the car for a certain period of time (usually 3-4 years). A comparable business model for BEV is battery leasing, for which the consumers purchase the car body but pay a monthly rate to lease the battery, which is the most expensive single component of a BEV. As for carsharing, it is a type of access-based consumption in contrast to purchase: consumers only pay each time when they use a shared car and they are charged by hours or even minutes. Although leasing and carsharing were not invented recently and have already been available in some countries for a while, they only gained momentum along with the general trend of access-based consumption and is still growing fast. The number of private leasing cars in the Netherlands increased by 61% in 2017 in comparison to 2016[6]. Carsharing is also quickly expanding worldwide: the annual growth rate of fleet and registered members is respectively 23% and 76% (Shaheen, Cohen and Jaffee, 2018).

Since battery technology at its current stage entails a barrier for widespread market penetration, existing mainstream business models may be insufficient to address these barriers. Deploying the same technology via different business models can lead to different economic outcomes (Chesbrough, 2010). In the case of EV, both leasing and carsharing can relieve financial burden brought by initial purchase price; they also reduce the uncertainties by shifting some risks away from consumers, such as battery technology becoming obsolete or residual price being unexpectedly low when trading at the second-hand market. Therefore, applying alternative business models may help in increasing EV penetration or even be the prerequisite for EV to be commercially viable. In fact, almost 80% of the BEVs in the US are currently leased instead of bought while the percentage is only 30% for the entire fleet[7], which implies that the share of leasing is much higher for EV than for Conventional Vehicles (CV). This seems to justify the need for empirical studies aiming to understand the impact of business models on EV adoption.

1.2. Research gap, goal and social relevance

There has been a myriad of studies concerning consumer preferences for electric vehicles in the transportation field. Most of them took the stated preference approach and focused on the attributes of the vehicles and the accompanying charging infrastructure. Another strand of

[6] https://www.trouw.nl/home/leasen-van-een-prive-auto-neemt-een-forse-vlucht~a84f7cc9/
[7] https://www.bloomberg.com/news/articles/2018-01-03/why-most-electric-cars-are-leased-not-owned

literature mainly looked into the influence of psychological factors on EV preference[8]. However, almost none of them explicitly mention the business model for adoption[9], which makes it impossible to disentangle and measure the impact of business model.

On the other hand, there are some studies coming from the management field that explore the impact of business models combined with sustainable technologies including EVs (Kley, Lerch and Dallinger, 2011; Budde Christensen, Wells and Cipcigan, 2012; Wells, 2013; Bohnsack, Pinkse and Kolk, 2014). Being explorative in nature, most of these studies either introduced a conceptual framework, discuss the possible impacts of business models in theory or conducted case studies. To the best of my knowledge, there have been no quantitative empirical studies which can give us insights regarding the pattern and size of the impact of business models.

To summarize, so far there has been no empirical studies conducted to quantitively study the consumer preference for alternative business models and how they can influence electric vehicle adoption. Therefore, the main goal of this thesis is to gain insight into consumer preferences for different business models in the context of electric vehicles and explore the impact of providing alternative business models on EV market share.

In order to achieve the goal, the thesis first starts with a literature review of studies on consumer preferences for electric vehicles in order to synthesize the existing findings which contributes to studies on EV adoption in general. We then devote two empirical studies to the business model of battery leasing and vehicle leasing. In the third chapter we investigate the choice of business model together with the choice of car type, which gives us insight into consumer preferences for these two business models. However, even if leasing would be the most preferred for BEV, this does not necessarily mean that offering more EV leasing options would lead to an increase in BEV sales; because those who prefer leasing may choose BEV anyway even when only buying is available. Therefore, chapter four is dedicated to exploring how the availability of alternative business models influence the choice of car type and in turn the market share of EV. Chapter five looks at the business model of carsharing and studies whether the deployment of electric shared cars can influence the decision of carsharing usage and car ownership. The final chapter discusses the overall conclusion and policy implication.

The insights derived from our results are valuable for both government and industry. If we can demonstrate the potential of business models, policy makers can take it into account in their decision-making. With one more policy instrument in the toolbox, government can implement a portfolio of policies (combined with other incentives such as tax rebate/purchase incentive) which suits the goal best. Car manufacturers can realize the added-value brought by business models by optimizing the provision of business models to both maximize profits and increase consumer experience. Companies which provide leasing and carsharing services can also benefit from the results regarding consumer preferences for leasing and carsharing when optimizing their level of service.

1.3 Research questions, theories and methods

This section introduces the sub research questions and the methods used to answer them. For all models applied to describe choice behavior in the empirical studies, the underlying theory is random utility maximization (RUM), which states that individual always chooses the alternative with the highest utility, while this utility is the sum of two components, namely a systematic utility and a random "error" unknown to researcher. The systematic utility is characterized by the important attributes of the alternative which are likely to play a role in decision making: in the case of vehicles, some examples of the commonly included attributes

[8] See Chapter 2 for a more detailed literature review on EV preferences studies.
[9] See (Glerum, Stankovikj and Bierlaire, 2014; Valeri and Danielis, 2015) for two exceptions.

include purchase price, fuel cost and vehicle performance. The formulation of the systematic utility is typically a linear combination of the attribute values. It is the dominant theory in the field of travel behavior modeling and more details can be found in Train (2003). However, several of its assumptions are often unrealistic in real life, and other theories have been proposed to relax these assumptions and increase behavioral realism. A prominent example is Prospect Theory (PT) (Kahneman and Tversky, 1979) and its features include reference-dependence, loss aversion and diminishing sensitivity. Another popular alternative theory in the choice modelling field is Random Regret Model (RRM) (Chorus, 2010; van Cranenburgh, Guevara and Chorus, 2015) which in essence also describes reference-dependent (reference points being other alternatives in the choice set) and loss averse (usually termed "regret aversion" in the RRM framework) behavior, albeit its function specification is different from PT. Since the dissertation is one of the earliest attempts in quantitively exploring and establishing the role of business models, I decided to not deviate from the orthodox RUM theory and the typical utility specification. However, since the decision of EV adoption differs from choosing a conventional fossil fuel car in multiple aspects (e.g. there are many uncertainties surrounding battery technology and everyday use of EV), consumers may use different decision rules in choices involving EV. Therefore, the exploration of these alternative decision rules in EV adoption choice behavior is definitely a potential future research venue.

All models are estimated using a dataset collected from a survey conducted in June 2016 among potential car owners in the Netherlands.

1.3.1 Study 1: literature review of consumer preferences for electric vehicles

In this chapter, we conduct a literature review regarding the studies on consumer preference for electric vehicle in order to have a full picture of the state-of-the-art on EV preference research and to identify the gaps. More specifically, the study aims to answer the following research questions:

- *How are EV preference studies conducted (methodology, modelling techniques and experimental design)?*
- *What attributes do consumers prefer when they choose among specific vehicles?*
- *To what extent do these preferences show heterogeneity? What factors may account for heterogeneity?*
- *What research gaps can be derived from the review and what recommendations can we give for future research?*

To gather research articles for the study, we used several search engines and databases as a start: Google Scholar, Web of knowledge, ScienceDirect, Scopus and JSTOR. The keywords used in searching were "electric vehicles" combined with "consumer preferences" or "choice model". Backward snowballing further expanded the number of relevant articles. Only studies after 2005 are included because they cover all the attributes used in pre-2005 research and use more advanced modelling techniques.

1.3.2 Study 2: Consumer preferences for innovative business models in electric vehicle adoption

This study investigates consumer preferences for business models in the context of electric vehicle adoption. We focus on the business model of battery leasing and vehicle leasing. In this study, the choice of business model is viewed as an extra decision made together with the choice of car type. Since leasing complements with the shortcomings of certain technologies (such as full battery electric vehicle), the rank of preference for leasing may differ depending on the choice of vehicle type. Furthermore, the preference is expected to be influenced by people's attitudes towards leasing.

This study attempts to answer the following research questions:

- *Which business models do consumers prefer (for different types of vehicles)?*
- *How do people's attitudes influence their preference?*

We estimated a mixed logit model and a hybrid choice model to respectively answer the first and second question. In this setting, some alternatives are correlated which violates the independent and irrelevant alternative assumption of multinomial logit model: the mixed logit model relaxes this assumption by allowing random parameters and error components (McFadden and Train, 2000). Hybrid choice model is the state-of-the-art method for estimating the influence of latent variables on choice behavior (Vij and Walker, 2016) which enables us to answer the second sub-question.

1.3.3 Study 3: The impact of business models on electric vehicle adoption: a latent transition analysis approach

This study takes a rather different perspective from Study 2. We focus on the choice of car type and aim to explore how the availability of business models influences this choice. Therefore, we investigate whether the provision of battery and vehicle leasing can increase the preference for battery electric vehicle. This impact on preference is expected to be heterogeneous among the population and dependent on each individual's initial preference when purchase is the only available business model. A discrete choice model which only estimates the average effects cannot uncover heterogeneous patterns of behavioral change. Therefore, we applied latent transition analysis on our choice data to reveal the impact of business model on different groups. Latent transition analysis is usually applied on panel data which is collected in multiple waves and each wave corresponds to a different point in time. Although our choice data was cross-sectional, each wave in our analysis corresponds to a distinct context offering a specific combination of business models: for example, the first wave of choices is made when buying is the only available business model, while for the second wave both battery leasing and buying are available.

This study answers the following research questions:

- *What is the aggregate impact of business models on EV preferences?*
- *How can consumers be classified based on their preferences for electric vehicles?*
- *How does the provision of business models affect EV adoption of different groups of consumers?*

In order to answer the research questions, we estimated a discrete choice model and a latent transition model. The discrete choice model reveals the aggregate impact of business model provision on the entire population, while the latent transition analysis allows an in-depth exploration into the heterogeneity of this impact.

1.3.4 Study 4: the impact of carsharing system characteristics on its potential to replace private car trips and reduce car ownership

This study looks at another business model namely carsharing. Compared to vehicle leasing, carsharing is one step further towards access-based consumption. Since consumers do not have to worry about the uncertainties surrounding battery degradation and residual value, carsharing can provide easy access to EV for those who have doubts for owning EV, which may help to realize the potential of EV in reducing emission to a fuller extent. In a broader context, many studies found that carsharing can also reduce car ownership and in turn the total number of cars on the road. Therefore, it is valuable to examine how the deployment of EVs in the shared car fleet would affect this potential of reducing car numbers.

This study answers the following research questions:

- *What is the impact of carsharing system attributes (especially the option of deploying electric vehicles in shared car fleet) on the intention of replacing private car trips and reducing car ownership?*
- *How can consumers be classified based on their preferences for carsharing?*
- *Is there any relation between car owners' intention of private trip replacement and car ownership reduction?*

We used the ordinal logit model to model the intention of replacing car trip and reducing car ownership. In order to identify different consumer groups, we adopted a latent class structure for the model.

Figure 1 illustrates the outline of the entire thesis. Since the thesis is a collection of four journal articles which were written and published independently, the structure presented in the introduction may appear to be more visible than in the separate chapters.

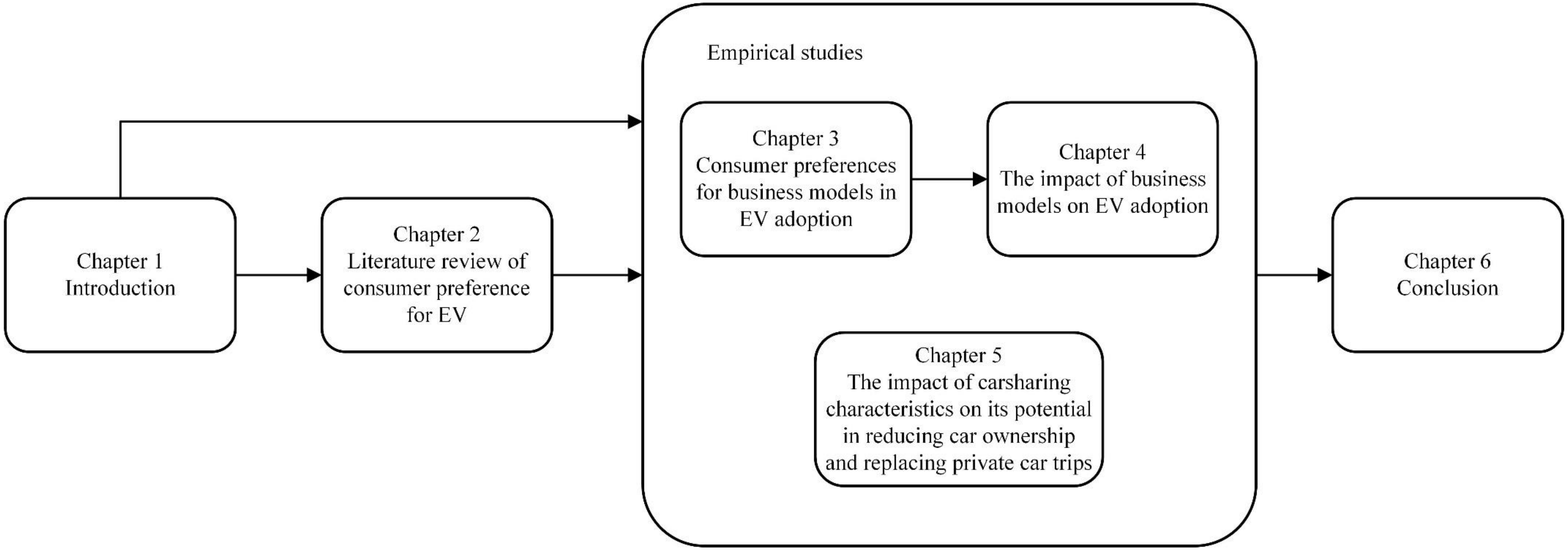

Figure 1. Organization of the dissertation

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2. Consumer Preferences for Electric Vehicles: a Literature Review

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: a literature review. Transport Reviews, 37(3), 252–275.
https://doi.org/10.1080/01441647.2016.1230794

Abstract

Widespread adoption of electric vehicles (EV) may contribute to the alleviation of problems such as environmental pollution, global warming and oil dependency. However, the current market penetration of EV is relatively low in spite of many governments implementing strong promotion policies. This paper presents a comprehensive review of studies on consumer preferences for EV, aiming to better inform policy makers and give direction to further research. First we compare the economic and psychological approach towards this topic, followed by a conceptual framework of EV preferences which is then implemented to organize our review. We also briefly review the modeling techniques applied in the selected studies. Estimates of consumer preferences for financial, technical, infrastructure and policy attributes are then reviewed. A categorization of influential factors for consumer preferences into groups such as socio-economic variables, psychological factors, mobility condition, social influence etc. is then made and their effects are elaborated. Finally, we discuss a research agenda to improve EV consumer preference studies and give recommendations for further research.

2.1 Introduction

Many governments have initiated and implemented policies to stimulate and encourage Electric Vehicle (EV) production and adoption (Sierzchula, Bakker, Maat, & Van Wee, 2014). The expectation is that better knowledge of consumer preferences for EV can make these policies more effective and efficient. Many empirical studies on consumer preferences for EV have been published over the last decades, and a comprehensive literature review would be helpful to synthesize the findings and facilitate a more well-rounded understanding of this topic. Rezvani, Jansson and Bodin (2015) give an overview of EV adoption studies; however, they only focus on individual-specific psychological factors which influence people's intention for EV adoption and only select some representative studies. Our review complements it in the following ways: firstly, we review a wider range of influential factors in EV adoption other than psychological constructs only; secondly, we present a comprehensive picture of current research by collecting all the available academic EV preference studies.

This literature review aims to answer the following questions: 1) How are EV preference studies conducted (methodology, modeling techniques and experiment design)? 2) What attributes do consumers prefer when they choose among specific vehicles? 3) To what extent do these preferences show heterogeneity? What factors may account for heterogeneity? 4) What research gaps can be derived from the review and what recommendations can we give for future research?

To gather research articles for the study, we used several search engines and databases as a start: Google Scholar, Web of knowledge, ScienceDirect, Scopus and JSTOR[10]. The keywords used in searching were *electric vehicles* combined with *consumer preferences* or *choice model*[11]. Many of these articles contain a brief review of existing research, which enabled backward snowballing. The articles used in this review were selected based on their relevance to the research questions. We only include studies after 2005 because they cover all the attributes used in pre-2005 research and use more advanced modeling techniques.

EVs come in different types and can be categorized into Hybrid Electric Vehicles (HEV) and plug-ins: HEVs have a battery which only provides an extra boost of power in addition to an internal combustion engine and increases fuel efficiency due to recharging while braking; while plug-ins can be powered solely by battery and have to be charged by plugging into a power outlet. Plug-ins can be further divided into Plug-in Hybrids (PHEVs, which are powered by both a battery and/or engine) or full Battery Electric Vehicles (BEVs). Our review focuses only on BEV and PHEV, since - unlike HEVs - they require behavioral changes as they require charging. However, studies on HEV were also included when they involve relevant factors which are not yet covered in BEV and PHEV preference studies.

This paper is organized as follows: Section 2 presents a conceptual framework for the review after comparing different methodological approaches and then discusses the modeling techniques of EV preference studies. Section 3 describes the importance of various attributes of EV in consumers' choices. Section 4 discusses the factors which are influential in EV preferences. The final section presents the main findings, an integrative discussion and a research agenda.

2.2 Conceptual framework and methodologies in EV preferences studies

2.2.1 Methodological approaches and conceptual framework of EV preferences studies

In this section we propose a conceptual framework for EV preferences based on which we organize our review. Before presenting the framework, we first briefly introduce its background.

[10]Last date of literature search was 15 Apr 2015.
[11] See section 2.1

Based on the differences in focusing factors, theories and models, studies concerning EV adoption can be roughly divided into two categories: economic and psychological. The most widely applied methodology among economic studies is discrete choice analysis in which EV adoption is described as a choice among a group of vehicle alternatives described by their characteristics or “attributes”. Consumers make decisions by making trade-offs between attributes. Economic studies focus on estimating the taste parameters for attributes which denote their weights in the decision. Psychological studies focus on the motivation and process of decision-making by examining the influence of a wide range of individual-specific psychological constructs (attitudes, emotion, etc.) and perceptions of EV on intentions for EV adoption. Their strength lies in uncovering both the direct and indirect relationships between these constructs and the intention. In contrast to economic studies, these studies generally ignore other vehicle options (Conventional Vehicles (CV) such as gasoline and diesel vehicles) and do not specify or systematically vary the EV attributes. Consequently, psychological studies only provide limited (if any) insight into how changes in the attributes of EV can lead to a shift in preferences for EV. Moreover, discrete choice analysis also allows the incorporation of psychological constructs, which enables a more comprehensive conceptual framework than that of psychological studies.

This review utilizes the framework applied in economic studies for two reasons: first, many governments or car manufacturers aim to increase EV adoption by improving EV attributes or the supporting service system (e.g. charging infrastructure, etc.), and discrete choice analysis – used by economic studies - is more suitable for evaluating the potential effectiveness of these policies or strategies. The second reason is that it can relatively easily incorporate factors and theories from psychological studies.

Figure 1 presents our framework. Vehicle adoption is essentially choosing a vehicle from the given set of alternatives. Although there are other possible decision rules, decision makers are most commonly assumed to choose the alternative that maximizes their utility. The utility of each alternative is generally assumed to be a linear combination of all the attributes of the alternative multiplied by a taste parameter that denotes the weight of the attribute for an individual. Choice data are used to calibrate discrete choice models by estimating the value of taste parameters in utility functions. To include preference heterogeneity (the value of taste parameters varies in the population) many choice studies include individual-related variables to capture heterogeneity. These variables either directly influence utilities or moderate the relationship between attributes and utilities.

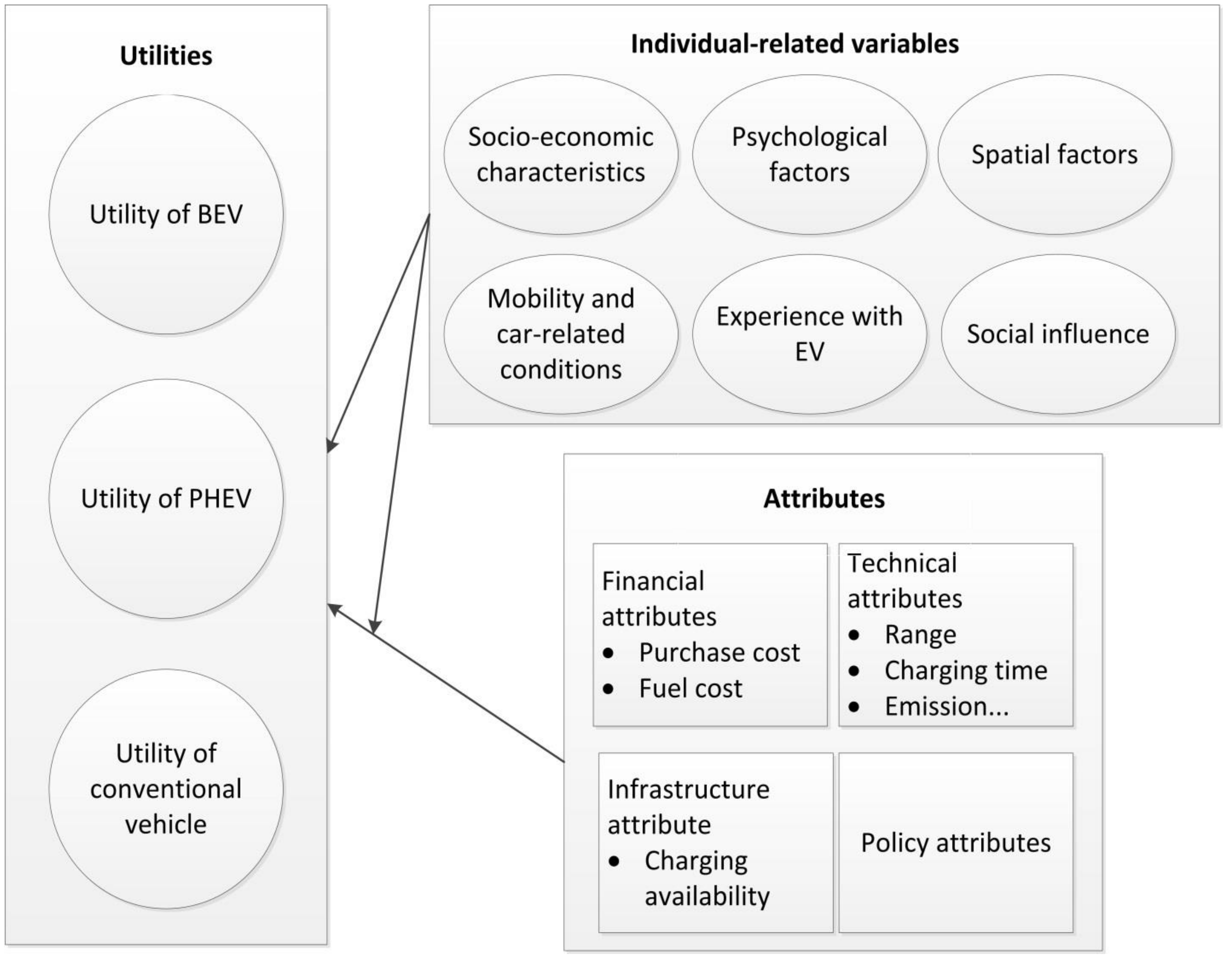

Figure 1. Conceptual framework of EV preference

2.2.2 Review of modeling techniques

We mainly focus on studies applying the economic approach, while other studies are also mentioned if their findings highlight additional factors and relationships. Table 1 gives an overview of the studies reviewed.

All studies are based on SP (Stated Preference) data due to the lack of a large-scale presence of EVs in the market. SP data is collected by choice experiments in which respondents making one choice from given set of alternatives. Attribute values vary between alternatives and can be hypothetical.

As for data analysis, the mainstream choice model has evolved: first, most studies only estimated the most basic MNL model (McFadden, 1974). However, MNL assumes Independence from Irrelevant Alternatives (IIA), which does not hold in most cases. Thus some studies used nested logit models to relax the restriction of IIA (Train, 2003). Nested logit models account for the correlation between alternatives by clustering alternatives into several “nests”: alternatives in the same nest are more similar and compete more with each other than with those belonging to different nests.

Table 1. Overview of studies

Author(s) (year)	Country	Time of data collection	Number of respondents	Number of choice tasks for each respondent	New vehicle alternatives included in given choice set[1]	Estimation model
Horne, Jaccard, & Tiedemann, 2005	Canada	2002-2003	866	4	NGV (Natural Gas Vehicle), HEV, FCV (Fuel Cell Vehicle)	MNL (MultiNomial Logit model)
Potoglou & Kanaroglou, 2007	Canada	2005	482	8	AFV(general), HEV	Nested logit model
Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 2008	Canada	2002	915HEV 1019FCV	18	HEV, FCV	MNL
Hidrue, Parsons, Kempton, & Gardner, 2011	USA	2009	3029	2	BEV	Latent class model
Mabit & Fosgerau, 2011	Denmark	2007	2146	12	AFVs including BEV, HEV	MXL (MiXed Logit model)
Musti & Kockelman, 2011	USA	2009	645	4	HEV, PHEV	MNL
Qian & Soopramanien, 2011	China	2009	527	8	BEV, HEV	Nested logit model
Achtnicht, Bühler, & Hermeling, 2012	Germany	2007-2008	598	6	AFVs including BEV, HEV	MNL
Daziano, 2012	Canada	Same as Horne et al. (2005)			NGV, HEV, FCV	HCM (Hybrid Choice Model)
Hess, Fowler, & Adler, 2012	USA	2008	944	8	AFVs including BEV	Cross-nested logit model
Molin, Van Stralen, & Van Wee, 2012	Netherlands	2011	247	8 or 9	BEV	MXL
Shin, Hong, Jeong, & Lee, 2012	South Korea	2009	250	4	BEV, HEV	Multiple discrete-continuous extreme value choice model
Ziegler, 2012	Germany	Same as Achtnicht et al. (2012)			AFVs including BEV, HEV	Probit model
Chorus, Koetse, & Hoen, 2013	Netherlands	2011	616	8	AFVs including BEV, PHEV	Regret model
Daziano & Achtnicht, 2013	Germany	Same as Achtnicht et al. (2012)			AFVs including BEV, HEV	Probit model
Daziano & Bolduc, 2013	Canada	Same as Horne et al. (2005)			NGV, HEV, FCV	Bayesian HCM
Hackbarth & Madlener, 2013	Germany	2011	711	15	AFVs including BEV, PHEV	MXL
Jensen, Cherchi, & Mabit, 2013	Denmark	2012	196	8	BEV	HCM
Rasouli & Timmermans, 2013	Netherlands	2012	726	16	BEV	MXL

Author(s) (year)	**Country**	**Time of data collection**	**Number of respondents**	**Number of choice tasks for each respondent**	**New vehicle alternatives included in given choice set[1]**	**Estimation model**
Bockarjova, Knockaert, Rietveld, & Steg, 2014	Netherlands	2012	2977	6	BEV, HEV	Latent class model
Glerum, Stankovikj, & Bierlaire, 2014	Switzerland	2011	593	5	BEV	HCM
Hoen & Koetse, 2014	Netherlands	2011	1903	8	AFVs including BEV, PHEV	MXL
Kim, Rasouli, & Timmermans, 2014	Netherlands	Same as Rasouli & Timmermans (2013)			BEV	HCM
Tanaka, Ida, Murakami, & Friedman, 2014	USA/ Japan	2012	4202/ 40000	8	BEV, PHEV	MXL
Helveston et al., 2015	USA/ China	2012-2013	572/ 384	15	BEV, PHEV, HEV	MXL
Valeri & Danielis, 2015	Italy	2013	121	12	AFVs including BEV	MXL

Note: 1. This column lists the included vehicle alternatives apart from conventional ones (gasoline, diesel).
AFV (general): AFV included as a single alternative without specifying fuel type
AFVs including…: Other AFVs (LPG, biofuel, flexifuel…) are also included as alternatives

Taste parameters in both MNL and nested logit model are fixed constants, implying that preferences do not vary across consumers, which is often unrealistic. In order to accommodate differences in preferences, the mixed logit model became common practice from about 2010: by assuming taste parameters to be randomly distributed, it captures preference heterogeneity albeit without offering explanations (McFadden & Train, 2000). Three methods are typically used to identify the source of heterogeneity:

- Traditional segmentation: interaction items between measured individual-specific variables and attributes (or alternative specific constant (ASC)) are added to the utility function to test for its statistical significance. Usually this is conducted in an explorative fashion: it has very little theoretical basis and conclusions are drawn solely based on p-values. The significance of variables is influenced by model specification since a variable may lose significance after controlling for its correlations with added variables.
- Identifying influential latent variables: The hybrid choice model (HCM) is the current state-of-the-art method for accounting for heterogeneity (Ben-akiva et al., 2002). It incorporates latent (usually psychological) variables which are measured by several indicators and assumed to be influenced by exogenous (e.g. socio-economic) variables. However, applying its insights to policymaking is rather difficult (Chorus & Kroesen, 2014).
- Categorizing consumers based on different preferences by estimating a latent class model (Boxall & Adamowicz, 2002), assuming that people can be classified into several classes: each class has a different preference profile, and class membership depends on individual characteristics. It is easy to use and interpret, but as with the HCM it is difficult to apply in policy making because it is not straightforward to locate target groups.

These more advanced models generally have a significantly higher model fit than the basic MNL model. It is however unknown how they compare with each other regarding model fit since none of the studies estimated multiple advanced models. Moreover, these models differ vastly regarding specific model structure and the number of parameters, which makes a comparison of model fit far from straightforward. Overfitting is also worth noting: choice studies rarely check the prediction reliability of their models and try to achieve higher model fit by using an excessive number of parameters, which may lead to the potential problem of overfitting.

2.3 A review of preferences for EV attributes

EV preference studies generally include the *financial, technical, infrastructure* and *policy attributes* for vehicle alternatives. In addition they include ASC in the utility function, capturing the joint effect of all the attributes of an alternative which are not included in the choice experiment. The ASC for EV is usually interpreted as a basic preference for EV compared to conventional cars when everything else is equal. Since different studies usually include different attributes, by definition the ASCs in these models cover different factors and cannot be directly compared.

This section presents an overview of the findings on the preferences for different attributes of EV. An overview of attributes (without policy attributes) can be found in Table 2. For each attribute, we first discuss its operationalization to see how it is defined and measured in the choice experiments, and then present its parameter significance. We also elaborate whether preferences vary among samples and provide some explanation for preference heterogeneity if applicable. Because there are many sporadic findings regarding the relationship between individual-related variables and the taste parameters of attributes, we only discuss those which are either reasonable/counter-intuitive/inspiring or repeatedly confirmed.

Table 2. Overview of financial, technical and infrastructure attributes

Attributes	Operationalization	References[1]
Purchase price	Price	All studies in Table 1
Operation cost	Price per 100 km	All studies in Table 1
	Fuel efficiency	
Driving range	Range after full charge	Chorus et al., 2013; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Hoen & Koetse, 2014; Mabit & Fosgerau, 2011; Mau et al., 2008; Molin et al., 2012; Qian & Soopramanien, 2011; Tanaka et, al., 2014; Rasouli & Timmermans, 2013; Kim et al., 2014 **Insignificant:** Hess et al., 2012;
	Maximum/minimum range	Bockarjova et al., 2014
	All-electric range (PHEV)	Helveston et al., 2015
Charging time	Time for a full charge	Bockarjova et al., 2014; Chorus et al., 2013; Hackbarth & Madlener, 2013; Hess et al., 2012; Hidrue et al., 2011; Hoen & Koetse, 2014; Rasouli & Timmermans, 2013
Engine power	Horsepower	Achtnicht et al., 2012; Horne et al., 2005
Acceleration time	Time from 0-100km/h	Helveston et al., 2015; Hess et al., 2012; Hidrue et al., 2011; Potoglou & Kanaroglou, 2007 **Insignificant:** Mabit & Fosgerau, 2011, Valeri & Danielis, 2015
Maximum speed	Speed (km/h)	Rasouli & Timmermans, 2013
CO_2 emission	Emission per km	Achtnicht et al., 2012
	Percentage relative to reference vehicle	Hackbarth & Madlener, 2013; Hidrue et al., 2011; Mabit & Fosgerau, 2011; Potoglou & Kanaroglou, 2007; Tanaka et al., 2014
Brand	Country origin of brand	Helveston et al., 2015
Brand diversity	Number of brands available	Chorus et al., 2013; Hoen & Koetse, 2014
Warranty	Period/range covered by warranty	Mau et al., 2008
Charging availability	Distance from home to charging station	Rasouli & Timmermans, 2013 **Insignificant**: Valeri & Danielis, 2015
	Detour time than to gas station	Bockarjova et al., 2014; Chorus et al., 2013; Hoen & Koetse, 2014
	Percentage of the number of gas stations	Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Horne et al., 2005; Mau et al., 2008; Potoglou & Kanaroglou, 2007; Qian & Soopramanien, 2011; Shin et al., 2012; Tanaka et al., 2014
	Presence in different areas	Molin et al., 2012; Jensen et al., 2013 **Insignificant**: Hess et al., 2012

Note: 1. If not marked, all references listed find the attribute significant. 2. As for studies which use the same dataset, only the earliest published study is listed here.

2.3.1 Financial attributes

Financial attributes refer to various types of monetary costs of vehicle purchase and use:

Purchase price is included in all the reviewed studies. Many studies used pivoted design for this attribute: price levels are customized and pivoted around the price of a reference vehicle stated by each respondent. Purchase price was found to have a negative and highly significant influence on the EV utility in all studies. In most of the studies this is explored as a linear relationship, with rare exceptions, for example Ziegler (2012) who attempted to capture the non-linear effect by using logarithms of the price.

Price preferences also vary among populations. Rasouli & Timmermans (2013) found that heterogeneity is particularly high when the price of EV is much higher than CV. Several studies discovered an income effect, namely that people with high incomes are less price-sensitive than others (Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Hess et al., 2012; Mabit & Fosgerau, 2011; Molin et al., 2012; Potoglou & Kanaroglou, 2007; Valeri & Danielis, 2015), while Jensen et al. (2013) found this effect to be insignificant. Preferred car size also plays a role in price sensitivity: Jensen et al. (2013) concluded that buyers of smaller cars have a higher marginal utility of price. People who choose used cars also find price to be more important (Hoen & Koetse, 2014; Jensen et al., 2013). Moreover, individuals who are more interested in the practical aspects of the car as opposed to design are less affected by price (Glerum et al., 2014).

Operation cost also appears in every study albeit in slightly different forms. Most studies use energy cost as the attribute: either cost per (100) km or both fuel efficiency and fuel price (Musti & Kockelman, 2011). Some studies also include regular maintenance costs (Hess et al., 2012) or combine it with energy costs as a combined operation cost attribute (Mabit & Fosgerau, 2011). These all negatively affect the decision to purchase a car, which gives EV an edge over CV since EV generally has lower energy costs (Mock & Yang, 2014). Jensen et al. (2013) found that the marginal utility of fuel cost for EV is much higher than for CV.

Again, people with higher incomes place lower importance on fuel cost (Helveston et al., 2015; Valeri & Danielis, 2015). However, Chinese respondents with higher income are more sensitive to high fuel costs (Helveston et al., 2015). This effect implies that in China the attraction of EV is reinforced since rich people who can afford EV also value the cost savings it brings in its daily operation.

Battery lease cost is only included in Glerum et al. (2014), which considers a business model different from one-time purchase. Similar to other costs, it has a negative impact on the purchase decision, as expected. In addition, people who have a more “pro-leasing” attitude are less sensitive towards lease cost. Valeri and Danielis (2015) also included an alternative with the option of battery lease but did not disentangle its effect from the impact of brands.

2.3.2 Technical attributes

Technical attributes describe the technical characteristics of the vehicle itself:

A relatively short *driving range* is considered to be one of the biggest barriers to the widespread adoption of EV. The most common operationalization is driving range with a full battery. An exception is Bockarjova et al., (2014), which included both range under normal and unfavorable circumstances. Range is found to have a positive and statistically significant effect on EV adoption decisions in the vast majority of studies. However, Hess et al. (2012) found this effect to be insignificant, which may be explained by the limited range used in their experiment (30-60 miles). Jensen et al. (2013) found that the marginal utility for driving range is much higher for an EV than for a CV, which is probably due to the large difference in range between these two car types. Following a meta-analysis, Dimitropoulos, Rietveld and van Ommeren (2013) proposed that preference for range may be sensitive to charging station density and charging time. In the case of PHEV, a longer all-electric range (the distance solely battery-powered) also increases the likelihood of purchase (Helveston et al., 2015).

The heterogeneity in the preference is higher when the range is significantly lower than the range of an average CV (~100 km) (Rasouli & Timmermans, 2013), which indicates a polarized preference towards the range of most current BEVs. People with a lower annual mileage have a lower preference for driving range (Hoen & Koetse, 2014). Households with multiple cars are less concerned about a relatively low EV range (Jensen et al. 2013), since they have a CV available for long distance trips. Franke, Neumann, Bühler, Cocron and Krems (2012) claimed that certain personality traits and coping skills for stress can relieve worries about the EV range. Direct experience with EV is also expected to be helpful in reducing “range anxiety”. Bunce, Harris and Burgess (2014) found that throughout a trial period drivers became more relaxed. However, Jensen et al. (2013) found people to value the EV driving range almost twice as highly once they had driven an EV for three months.

Recharging time is found to be significant in all the studies that included it. However, apart from Bockarjova et al., (2014), none of the studies distinguished between slow and fast charging. Recharging time depends on the power of the charging post and the battery capacity. For everyday purpose EV uses *slow charging* at home or at work which takes around 6-8 hours for a full charge. As for recharging during long trips, fast chargers can fill the battery up to 80% within 15-30 minutes. In other words, “charging time” varies greatly depending on the conditions.

Performance is usually represented by engine power, acceleration time or maximum speed. Consumers are generally found to prefer better performance. However, acceleration time is found to be insignificant in Mabit and Fosgerau (2011) and Valeri and Danielis (2015) since heterogeneous preferences among the population may cancel each other out: males have a significant preference for faster acceleration while females prefer slower acceleration (Potoglou & Kanaroglou, 2007; Valeri & Danielis, 2015). Potoglou and Kanaroglou (2007) also found that single people value shorter acceleration time more.

Although emissions of BEV while driving are absent, many studies still set different levels of *CO_2 emission* for EV in the choice experiment, representing the emissions of electricity generation. Choice experiments either directly use absolute CO_2 emission per kilometer or the percentage relative to a gasoline vehicle. Hackbarth and Madlener (2013) found that for environmentally-friendly people the same amount of emission brings higher disutility.

Brand and diversity: Valeri and Danielis (2015) included the car model in the label in the choice experiment; however the effect was not separated from fuel type. Helveston et al. (2015) found that people prefer brands from certain countries and the preference order differs between countries. Chorus et al. (2013) and Hoen and Koetse (2014) found that having more EV models available on the market increases the probability of choosing an EV. It can be seen as an indicator of EV market maturity and thus influence people’s perception of uncertainty. This may account for the low sales of EV as at present there only a few brands with EVs for sale, and some potential EV buyers probably do not like the specific brands or prefer more options to choose from.

Warranty is found to affect EV adoption positively (Mau et al., 2008). Jensen et al. (2013) found the influence of battery life to increase after respondents participated in a 3-month trial period of EV but both effects are non-significant. This issue is expected to be relevant because there are a lot of uncertainties regarding battery life and consumers may prefer more certainty for these aspects. Based on the existing results the significance of a warranty’s effect remains unclear.

2.3.3 Infrastructure attributes

Infrastructure attributes focus on the availability of the charging infrastructure. There is not yet consensus regarding its operationalization: some studies show the density of charging stations relative to gas station; Rasouli and Timmermans (2013) use the distance from home to the closest charging station, while others present the presence of a charging station in different areas: at home, at work or in shopping malls, etc.

In most studies it has a significantly positive effect, possibly because more charging facilities save time and search cost for users as well as relieving their range anxiety as well. Achtnicht (2012) found the effect to be non-linear with a diminishing marginal utility. Charging posts in different activity locations are preferred by certain groups: for example, Jensen et al. (2013) found that long distance commuters value chargers in work places significantly more than others, and prefer a higher density of charging stations (Potoglou & Kanaroglou, 2007).

The reviewed studies do not however differentiate slow charging posts from fast charging stations, while– as explained above - these two serve different purposes. Public slow charging posts are mainly situated in workplaces or shopping malls where parking is for longer periods, while fast charging stations are mostly located on highways (also in cities but only for emergency) to support longer EV trips. Most importantly, unlike CV which requires regular visits to gas stations for refueling, EV allows users to rely on home charging as long as one's daily distance is within the EV's range, which applies to most people (Tamor, Moraal, Reprogle, & Milačić, 2015). Bunce et al. (2014) reported that after a trial period, users preferred recharging at home to refueling at petrol stations due to its convenience. In contrast, since EVs mostly rely on slow charging, it is almost impossible to use an EV regularly if there is no charging facility at home or work. Whether respondents were fully aware of this was not clear.

2.3.4 Policy attributes

Table 3. Overview of policy attributes

Policy	Studies which find it effective	Studies which find it ineffective
Pricing policies: One-time reduction		
Reduce/exemption of purchase tax	Hess et al., 2012; Potoglou & Kanaroglou, 2007	
Reduce purchase price	Glerum et al., 2014; Mau et al., 2008	Hackbarth & Madlener, 2013; Qian & Soopramanien, 2011
Pricing policies: usage cost reduction		
Reduce/exemption of road tax	Chorus et al., 2013; Hackbarth & Madlener, 2013; Hoen & Koetse, 2014	
Free parking		Hess et al., 2012; Hoen & Koetse, 2014; Potoglou & Kanaroglou, 2007; Qian & Soopramanien, 2011
Reduce toll		Hess et al., 2012
Land-use policy		
Access to HOV (High Occupancy Vehicle)/express/priority/bus lane	Hackbarth & Madlener, 2013; Horne et al., 2005	Hess et al., 2012; Hoen & Koetse, 2014; Potoglou & Kanaroglou, 2007; Qian & Soopramanien, 2011

Policy attributes include different policy instruments for promoting EV adoption. If the preference parameter for a certain policy attribute in the final choice model is significant, then the policy can be regarded as potentially effective. Five pricing policies were tested in the reviewed studies. Table 3 gives an overview of their findings.

Regarding one-time price reducing policies, *reducing purchase tax* is significant in all cases while *reducing purchase price* is only significant 2 out of 4 times. The difference can be most clearly seen in contrast to Hess et al. (2012): a \$1000 tax reduction is significantly positive while a \$1000 price reduction is not significant. This can possibly be due to the higher symbolic value attached to a higher priced car. Gallagher & Muehlegger (2011) also found that the type of tax incentive offered is as important as the generosity of the incentive.

As for usage cost reduction policies, *annual tax reduction* seems to be the only significant policy, while *free parking* and *toll reduction* are not significant in any of the studies that explored their effects. The effectiveness of different types of tax reduction reflects the difference in perceptions people have towards taxes versus other expenses.

As for the only non-financial policy tested, the effectiveness of *giving EV access to HOV lanes* remains ambiguous. There may be several reasons for the contradictory findings and lack of significance of potential non-financial policy instruments. First, the location of the data collection may play a role, people living in cities or regions without serious traffic congestion do not value access to HOV lanes much if at all; in addition, good availability of parking spaces and cheap or free parking are likely to lead to indifference towards dedicated and free parking space (Potoglou & Kanaroglou, 2007). Second, people living in places where there are no HOV lanes (Potoglou & Kanaroglou, 2007; Qian & Soopramanien, 2011) may have difficulty perceiving its benefits. Third, the polarized preferences of different groups could lead to an insignificant parameter when considering the entire sample. EV policy incentives which aim to encourage the substitution of CV by EV could have the unintended rebound effect that households increase the number of cars. Holtsmark and Skonhoft (2014) warned about this phenomenon in Norway's case. De Haan, Peters and Scholz (2007) did not find this effect for HEV.

2.3.5 Dynamic preference

Choice studies assume that preferences are stable; however, for EV preferences this is untrue for two reasons: first, EV only became available recently and different groups of people will adopt EV successively depending on their acceptance of innovation. People who enter the market at a different point in time are expected to have different preference profiles, therefore the preferences of consumers may vary over time (Rogers, 2003). Second, since EV is still relatively new and unfamiliar to most people and is continuing to develop, people's preferences are expected to evolve along with technological progress, familiarity with EV, market penetration, social influence, etc. If preferences indeed change significantly, the results of EV preference studies that assume static preference are only valid for a limited period of time.

Several studies stressed the importance of dynamics and each focused on one preference-changing factor: Maness and Cirillo (2011) assume dynamic preference due to *technological advancement* by setting different attribute levels for five consecutive years, forming a "pseudo longitudinal" data set. Motivated by the innovation adoption theory of Rogers (2003), Bockarjova et al. (2014) assigned people into five categories according to their *expected market entry time* and they are found to have different preference profiles. Mau et al. (2008) concluded that preference dynamics can also be caused by changes in the *EV market share*. Rasouli and Timmermans (2013) and Kim et al. (2014) found that *social influence* (EV adoption rate in an individual's social network) also changes people's preference for EV, although the effect is minor. However, these studies only explored one factor separately and did not investigate the combined effect of several possible sources of dynamics.

2.3.6 Conclusion

Financial, technical and infrastructure attributes are found to have a significant impact on EV choice and this is supported by the vast majority of studies in which they are included. As for policy incentives, tax reduction policies are effective while the effect of other policies (pricing and other) remains controversial. There is preference variance regarding many attributes and several individual-related characteristics have been identified which could account for this.

2.4 Factors accounting for heterogeneous EV preferences

In this section, we focus on individual-related variables which are found to have an impact on the general preference for BEV and PHEV and attempt to explain part of the taste heterogeneity. Table 4 presents an overview of the main factors explored in previous studies and related findings. One point worth noticing is that almost all individual-related variables are found to be insignificant in at least some studies and excluded in the final model; therefore we only list cases in which they are found to be significant.

2.4.1 Socio-economic and demographic characteristics

Socio-economic and demographic characteristics are the categories of individual-related variables most often included in choice studies; however, findings on their effect on EV preference are divergent. For all important socio-economic and demographic variables including gender, age, income, education level and household composition, it is so far unclear whether their effects are positive, negative or significant at all, since there is supporting evidence for all claims (see Table 3). The value and even the direction of their impacts are also sensitive to modeling choices: for example, in Rasouli & Timmermans (2013), the direction of the impact of the gender variable is different in two models based on the same dataset.

2.4.2 Factors from psychological theories

Psychological theories use a different set of factors to explain behavior including perceptions, attitudes, norms, etc. Huijts, Molin and Steg (2012) provided a framework which integrates most of the main psychological theories and factors relevant for sustainable technology acceptance/adoption. Choice studies also attempt to incorporate some of these constructs for a more comprehensive model with higher explanatory power.

Since EV adoption is considered to be motivated by environmental concerns, a personal norm in environmentally-friendly behavior is most often included and found to be positively related to a preference for EV. It is worth noting that its measurement differs among choice studies: most use indicators including environmental concerns and environmentally-friendly behavior, Daziano and Bolduc (2013) measure respondents' awareness of transport problems and support for transport policies. Kim et al. (2014) is the only one which measures the specific perception of EV as an environmentally-friendly vehicle.

As for perception variables, they can be useful to cover the aspects which are not included as attributes in the choice experiment. Kim et al. (2014) found that concern for value, battery and technological risks all contribute negatively to the probability of choosing an EV.

EV adoption is sometimes framed as an innovation adoption behavior due to the novelty of modern EV. The theory of innovation diffusion (Roger, 2003) suggested that innovativeness of an individual has a positive effect on EV adoption, which was confirmed by a few choice studies. Various psychological studies also concluded that uncertainty for technical progress has a negative impact on the intention to adopt an EV since EV is either considered as a "car of the future" (Burgess, King, Harris, & Lewis, 2013; Caperello & Kurani, 2011) or a "work in progress" (Graham-Rowe et al., 2012).

Table 4. Individual-specific variables influential for EV preference

Factors	Specific variables	Studies which find it has significant positive effect	Studies which find it has significant negative effect
Socio-economic and demographic variables			
Gender	Male	Kim et al., 2014; Rasouli & Timmermans, 2013	Jensen et al., 2013; Qian & Soopramanien, 2011; Rasouli & Timmermans, 2013
Age		**PHEV**: Musti & Kockelman, 2011	Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Qian & Soopramanien, 2011; Ziegler, 2012
		Non-monotonous: Rasouli & Timmermans, 2013	
Income		Qian & Soopramanien, 2011; Rasouli & Timmermans 2013; **PHEV**: Musti & Kockelman, 2011	Helveston et al., 2015 (US) **PHEV**: Helveston et al., 2015 (US)
Education level		Hidrue et al., 2011; Kim et al., 2014 **PHEV:** Hackbarth & Madlener, 2013	
		Non-monotonous: Rasouli & Timmermans, 2013	
Household composition	Household size	Qian & Soopramanien, 2011	
	Number of kids	Kim et al., 2014; Rasouli & Timmermans, 2013	Qian & Soopramanien, 2011
	Number of drivers in household		Qian & Soopramanien, 2011
Psychological factors			
Pro-environmental attitude		Achtnicht et al., 2012; Daziano & Bolduc, 2013; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Jensen et al., 2013; Kim et al., 2014; Ziegler, 2012 **PHEV**: Hackbarth & Madlener, 2013	
Concern for battery			Kim et al., 2014
Perception of high expense			
Concern for technical risk			
Innovativeness		Bockarjova et al., 2014; Hidrue et al., 2011; Kim et al., 2014	
Car as a status symbol		Helveston et al., 2015 (US)	Helveston et al., 2015 (CN)
Mobility and car-related condition			
Current car Condition	Car owner	Qian & Soopramanien, 2011	
	Second-hand car	Jensen et al., 2013	
	Small or mini	Jensen et al., 2013	
	Number of vehicles	Helveston et al., 2015 (Only in China); Jensen et al., 2013; Qian & Soopramanien, 2011; Ziegler, 2012	**PHEV**: Musti & Kockelman, 2011
Expected car condition	Small or mini	Hackbarth & Madlener, 2013; Hidrue et al., 2011	
	Horsepower		Ziegler, 2012
	Driving range	Ziegler, 2012	
Current mobility habit	Percentage of urban trips	Hackbarth & Madlener, 2013	
	Annual mileage	Ziegler, 2012 (expected mileage)	Hoen & Koetse, 2014
	Frequency of long trips	Hidrue et al., 2011	
	Commuting distance		Qian & Soopramanien, 2011
	Commuting frequency		**PHEV**: Hoen & Koetse, 2014

Factors	Specific variables	Studies which find it has significant positive effect	Studies which find it has significant negative effect
Spatial variables			
Charging capability	Having charging facilities at home	Hackbarth & Madlener, 2013; Helveston et al., 2015 (China); Hidrue et al., 2011; Hoen & Koetse, 2014 **PHEV**: Hackbarth & Madlener, 2013	
	Having a garage		Valeri & Danielis, 2015
Living in urban area		**PHEV**: Musti & Kockelman, 2011	
Countries and regions		Tanaka et al., 2014; Helveston et al., 2015	
Experience			
Trial period			Jensen et al., 2013
Social influence			
Market share		**HEV**: Mau et al., 2008	
Market share in social network		Kim et al., 2014; Rasouli & Timmermans, 2013	
Positive reviews			

Note: If not marked, the effect is on BEV preference.

Apart from environmental friendliness and innovativeness, other psychological constructs are also expected to have impacts on EV adoption. Dittmar (1992) and Steg (2005) identified that instrumental, hedonic and symbolic motives influence car purchase and use. Emotions are also found to be significant in some explorative research (Graham-Rowe et al., 2012). These variables are rarely included in choice studies on EV preference. The only example is Helveston et al. (2015) who investigated the symbolic value of BEV: in the US people who attach high symbolic value to their vehicle are more prone to purchasing an EV implying that EV symbolizes high social status. In China it is the opposite case.

So far, most studies incorporate psychological factors separately instead of a complete set of constructs in psychological theories such as the theory of planned behavior (Ajzen, 1991) or other integrative models proposed specifically for pro-environmental or sustainable technology acceptance behavior (Bamberg & Möser, 2007; Huijts, Molin, & Steg, 2012). Should future research wish to add more psychological factors, two points are worth noting: first, it is important to avoid the overlap with factors which are already covered by choice experiments; secondly, the researcher should control for correlation(s) between different psychological constructs.

2.4.3 Other variables which are less commonly included

Mobility, residence, and car-related condition

A person's EV preferences have also been found to be related to their mobility pattern, residential location and the characteristics of their current and expected car. These variables are however hardly independent as they are usually correlated with socio-economic and psychological factors. Section 4.4 provides a further discussion on this.

Experience

Knowledge of and exposure (through test drive, trial period, etc.) to EV are expected to have an impact on preferences. Jensen et al. (2013) is the only two-wave choice study including an EV trial period. They concluded that exposure to EV through a 3-month trial confirmed consumers' worries for EV and had a negative impact on their preference for EV. However, Woodjack et al. (2012) found that drivers gradually adapted their own behavior to fit the characteristics of EV during the trial period. Bühler, Cocron, Neumann, Franke and Krems (2014) concluded that experience had a significant positive effect on the general perception of EV and the intention to recommend EV to others, but not on attitudes and purchase intentions.

Social influence

An individual's decisions are expected to be influenced by the behavior of people in their social network (Kahn, 2007; Lane & Potter, 2007) and social norms which can be regarded as the behavior of the collective society (Araghi, Kroesen, Molin, & van Wee, 2014). Several qualitative studies found that social influence plays an important positive role in EV promotion (Axsen & Kurani, 2011; Axsen, Orlebar, & Skippon, 2013). Among choice studies, the influence of an individual's social network on HEV adoption has been demonstrated (He, Wang, Chen, & Conzelmann, 2014; Hsu, Li, & Lu, 2013). Social norm has also been found to be significant: a higher EV market share increases EV preference (Mau et al., 2008). Two studies (Rasouli and Timmermans (2013) and Kim et al. (2014)) investigated social influence in EV preference studies. As proxy variables for social influence, they used EV market share among different groups (friends and acquaintances, larger family, colleagues) and the nature (positive or negative) of general public reviews about EV. Both have a significant although minor impact on EV preference.

2.4.4 Correlation between variables

Most studies explore the interaction between individual-related variables and preference parameters separately without controlling for the correlation between different categories of individual-related variables. One exception is the correlation between psychological factors and other variables: Kim et al. (2014) found psychological factors to be related to socio-economic characteristics, Daziano & Bolduc (2013) with mobility habits and Jensen et al. (2013) with car condition. These studies apply HCM which contains a structural model and facilitates the exploration of relationships between latent psychological constructs and other personal characteristics.

There are certainly more expected correlations: for example, residential locations, mobility habits and car-related conditions are related to socio-economic characteristics; personal norm can also be influenced by social norms (Doran & Larsen, 2016). If these correlations are not controlled for in the final model, the model may suffer from self-selection bias and arrive at incorrect estimates. This may also be the reason for the contradictory findings regarding the effect of socio-economic characteristics on EV preference.

However, including all the variables mentioned above and controlling for all possible correlations may lead to an excessively complicated model and overfitting. Deciding which variables to choose depends on the goal of the research: if one aims to quantify the real effects of variables on EV preference in order to identify the potential factors for policy intervention, correlations should be modeled to derive an accurate effect size. On the other hand, if the study is a market segmentation which aims to study the characteristics of target customers for EV, then only the variables of interest need to be included.

2.4.5 Conclusion

In general, the effect of individual-specific variables on EV preference remains an open question. Psychological variables are the exception and have a proven stable effect, shown by several studies. For socio-economic and demographic variables, the impact is unclear and sensitive to small changes in model specification. The direction of the effect is also ambiguous since existing evidence is contradictory. Other variables are only included in a few studies, therefore their effects are as yet inconclusive. In most cases, the correlation between all these variables has not been controlled for to avoid self-selection bias. More research is definitely necessary to clarify these currently fuzzy relationships and other methods are needed to add more rigor and confidence to the results.

2.5 Conclusions, discussion and research agenda.

2.5.1 Main findings

We conduct the literature review in order to identify which attributes of EV and its service system have an impact on the utility of EV, including vehicle attributes, infrastructure system and EV promotion policies. We also aim to find out which individual-related variables affect one's preference for EV. Most research which investigated both of these two topics applied stated choice method since it provides a framework which can easily accommodate the impact of both vehicle attributes and individual characteristics on EV preference.

The impact of financial and technical attributes of EV on its utility is generally found to be significant, including its purchase and operating cost, driving range, charging duration, vehicle performance and brand diversity on the market. The density of charging stations also positively affects the utility of EV, which demonstrates the importance of charging infrastructure development in promoting EV. As for the impact of incentive policies, tax reduction (either purchase tax or road tax) is most likely effective, while there is not yet evidence supporting the effectiveness of other usage cost reduction such as free parking and toll reduction. The findings regarding giving EV access to priority lane vary for studies conducted in different regions. The preferences for the above attributes are mostly heterogeneous and can partially be accounted for by various individual-specific characteristics.

We also synthesized findings regarding the direct effect of various clusters of individual-related variables on one's general preference for EV. The effect of psychological factors is proven to be stable by most studies if included. The results regarding the effect of socio-economic and socio-demographic variables are contradictory thus their effect remains ambiguous. The impact of mobility and car-related conditions of spatial variables, experience with EV and social influence is explored by only a few studies. Although these variables are usually found to be significant, it is still too early for a definitive conclusion. When applying these results it is important to keep in mind that the way in which choice analysis approaches this topic generally lacks methodological rigor since many of them did not control for correlation between these individual-related variables, which may lead to self-selection bias and incorrect estimates for their direct effects.

2.5.2 Discussion

In this section, we provide a brief integrative discussion regarding the state-of-the-art of EV preference studies. From the conclusion we see that existing studies have generally achieved the same conclusion regarding the significance of financial, technical and infrastructure attributes. As for the effectiveness of incentive policies and the influence of individual-related variables on preferences, hardly any consensus has been reached. We now highlight three issues regarding the general setting and assumption of the reviewed studies which may influence the reliability of their results and conclusions:

First, we think the impact of uncertainty on preference has been insufficiently studied. There have been many other studies in the transportation field highlighting the role of uncertainty, for example focusing on the inclusion of travel time variability in travel behavior studies (Li, Tu & Hensher, 2016). However, all reviewed EV preference studies investigate preferences for alternatives with fixed attribute values even though there are many uncertainties surrounding

EV, including battery life, charging facility availability (whether it is occupied by others when needed), depreciation, etc. Moreover, exploratory studies have already found that uncertainty is one of the main barriers for EV adoption (Egbue & Long, 2012). Therefore, excluding the role of uncertainty in choice experiment design and choice model selection may risk reducing realism of choice tasks and ignoring an important factor which affects preference.

Second, most literature did not particularly specify the context of car type choice while it may have an impact on preference. For example, all surveyed studies except Hoen & Koetse (2014) either only explored preferences when buying a new car or did not distinguish whether the expected purchase was a new or second-hand car. Apart from Chorus et al. (2013), none of the studies clarify whether the expected purchase was financed as a private or company car. Furthermore, all reviewed studies only focused on vehicle purchase choice, while other forms of EV adoption may also take place as more mobility business models are becoming widely available, such as private leasing, carsharing, etc.

Third, it is important to realize that all the studies we found used SP data. Due to the low market share of EV, we can hardly gain any information regarding the unique attributes of EV from actual market data and stated choice is the most commonly used form of data in this case. However, there may be discrepancies between stated choices and real behavior in actual market, which are termed as "hypothetical bias" (Beck, Fifer & Rose, 2016). The hypothetical bias may even be accentuated in the case of EV adoption choices since many consumers are not familiar with EV alternatives and its unique attributes (Hess & Rose, 2009). Therefore, studies based on SP data are generally considered to be of less value for estimating market shares, but can still be informative regarding the relative importance of factors for choices (Ben-Akiva et al., 1994). These implications have to be taken into consideration in the interpretation and application of the results of EV preference studies using SP data.

2.5.3 Research agenda

In this section we call for further research based on the methodological and content related limitations of the existing studies.

2.5.3.1 Improvements on future studies applying discrete choice methods

Regarding experimental design, as stated above the common operationalization of attributes concerning charging are flawed and should be closer to actual EV use patterns in future choice studies. There are also a wide range of potential policy instruments which can be tested, such as improving home charging availability for people without dedicated parking space, providing dedicated public parking space for EV, closing central urban areas for conventional vehicles, assigning car plates without going through a lottery as is the case for CV buyers (already implemented in Beijing, see Zhao, Chen, & Block-Schachter, 2014), etc. Local conditions have to be taken into consideration when choosing the policy attributes to be tested (for example, if traffic congestion is not serious then granting HOV lane access tends to be inefwwwwsfective). Moreover, in addition to the main effect of increasing sales, potential rebound effects also have to be examined as discussed above.

As for modeling, the interaction effects between several relevant attributes e.g. driving range and charging station availability, driving range and charging time, etc. is worth exploring. As for establishing the relationships between individual-related variables and taste parameters, more studies and rigorous methodologies are needed to corroborate the conclusions, such as testing robustness by using different utility functions, applying models which allow indirect relationships apart from direct ones such as structural equation modeling, etc..

Regarding data collection, so far all the EV preference studies are based on SP data. Since the first mass-produced EV entered the market in 2011 and sales have been picking up in several countries (e.g. Norway, Netherlands, etc.), Revealed Preference (RP) data will become available in the near future. RP data can be combined with SP data in choice model estimation as a source of validation and ASC correction for choice models based on SP data (Axsen, Kurani, McCarthy, & Yang, 2011).

2.5.3.2 Rethink common assumptions in research

Because all the existing literature investigates EV preference ignored *uncertainties* underlying EV adoption decisions (see above), we recommend that future research investigates the way in which uncertainty influences decisions and quantifies its impact by explicitly incorporating it into a choice experiment, and to use different choice models such as regret models (Chorus, 2010) which may be more suitable for decision making under uncertainty than random utility maximization models.

The over-arching assumption in the existing literature is that preferences for EV are static and only a few studies considered *preference dynamics*. Future research could explore better ways to elicit preference variation along with changing social influence, ongoing public debates regarding sustainability issues, technical progress and EV market share changes (innovation adoption) by collecting panel data and integrate these dimensions into a general framework for preference dynamics which can be implemented in system simulations such as agent-based models.

We also call for more attention for the *decision process* of consumers. Choice models assume that the process of decision making is a black box and that it is rational, while this hardly holds in reality. Klöckner (2014) described an EV adoption decision-making process which describes the volatility of intention over 2 months. Results contradict the implicit assumption of fixed individual preference in most studies. The extent to which this affects choice model results is currently unknown. Further research can start by exploring how consumers process information when they purchase EV and taking this into account when analyzing preferences based on choice data. This would provide more accurate estimations of model coefficients and different policy advice targeting different stages of a decision process.

2.5.3.3 New perspectives, factors and topics

Adopting a time geography perspective (e.g. Neutens et al., 2008; Lee and Kwan, 2011; Farber et al., 2013) may lead to new insights regarding the effect of activity patterns on EV preferences. Existing research explores the relevance of activity patterns indirectly by including one or a few crude measures such as daily travel distance and linking these with attributes such as driving range and charging availability). Time geography allows for a more integrative and systematic exploration of constraints imposed by activity patterns. For example, the limited range of EV, charging time and density of charging stations imply constraints and may impact the time-space prisms when driving EV. Researchers can measure the impacts of the use of EVs in their different forms and with different characteristics on these prisms, and explore to what extent destinations fall out of the accessible area permitted by EV and violate the preferred activity patterns of people.

Studies on the effect of *direct experience* with EV are not abundant and provide contradictory results. The increase in demonstration projects and car-sharing programs enables people to encounter EV in different ways. The effect of different exposure duration (from one ride to a 3-month trial period) and types (car-sharing, trials, electrified public transport) on both the perception of EV attributes and purchase intention of EV are worth exploring. Another intriguing topic is the interaction between one’s own experience and social influence.

The potential role of *business models* in facilitating EV adoption has been largely overlooked. A stylized economic model (Lim, Mak, & Rong, 2015) found that the option to lease an EV battery can increase the preference for EV. There are a wide variety of business models in addition to battery lease and their effects should be further explored.

Up to now studies have only focused on EV adoption while *EV use behavior* has hardly been investigated. EV adoption and EV use may each be influenced by different factors. An intriguing topic is the usage pattern of EV in households with multiple vehicles (both EV and CV) and how that evolves over time. Moreover, ignoring EV use after adoption may lead to a serious bias when evaluating policy effects. For example, Shanghai has a strict license plate auction policy (average price 10,000 euro, success rate ~8%) while EV adopters are guaranteed license plates free of charge. This indeed leads to a higher rate of EV adoption; however, some people may use this policy to obtain a license plate: they buy a PHEV and drive it as a conventional vehicle and never recharge the battery[12]. These PHEV adoptions do not realize their potential benefits. Therefore, EV use needs to be studied in tandem with adoption to capture the full effect of policies.

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Appendix: List of acronyms

AFV	Alternative Fuel Vehicle
BEV	Battery electric vehicle
CV	Conventional vehicles
EV	Electric Vehicles
FCV	Fuel Cell Vehicle
HCM	Hybrid Choice Model
HEV	Hybrid electric vehicle (non plug-in)
HOV	High Occupancy Vehicle
MNL	MultiNomial Logit
MXL	MiXed Logit model
PHEV	Plug-in Hybrid Electric Vehicle
RP	Revealed Preference
SP	Stated Preference

3. Consumer preferences for business models in electric vehicle adoption

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Abstract

Successful market penetration of electric vehicles may not only rely on the characteristics of the technology but also on the business models available on the market. This study aims to assess and quantify consumer preferences for business models in the context of Electric Vehicle (EV) adoption. In particular, we explore the impact of attitudes on preferences and choices regarding business models. We examine three business models in the present study: battery leasing, vehicle leasing and mobility guarantee. We design a stated choice experiment to disentangle the effect of business models from other factors and estimate a hybrid choice model. According to the results, the preferences for business models depend on the vehicle type: for battery electric vehicle (BEV), vehicle leasing is the most preferred option and battery leasing is the least preferred, while for conventional cars (CV) and plug-in hybrids (PHEV) the traditional business model of full purchase remains more popular. The attitudes of pro-convenience, pro-ownership and pro-EV leasing are all significantly associated with the choice of business models. As for mobility guarantee, we do not find any significant effect on utility. Finally, we discuss the implications for business strategy and government policy derived from our results.

3.1. Introduction

Road transport, which is mainly powered by fossil fuels, contributes to a wide range of sustainability problems, such as global warming, environmental pollution and oil dependency, etc. Substituting cars powered by internal combustion engines with electric vehicles (EV) at a large scale is expected to be a potential solution to the above problems. However, despite the effort of car manufacturers and strong promotion of many governments, EV sales remain rather low and its potential benefits are not fully realized. Apparently, the environmental benefits for society brought by EV are not highly valued by many consumers and are insufficient in itself to achieve a high market share (Siegel 2009). The unattractiveness of EV for the mainstream market in comparison to conventional vehicles can be mainly attributed to the following shortcomings (Liao et al. 2017). First, the purchase price of EV is considerably higher in most countries due to the high battery costs. Second, the high amount of uncertainties surrounding EV: since EV applies relatively novel technologies, there are lots of uncertainties involved regarding issues such as battery life and speed of technological improvement, all of which have an impact and pose risks on the residue value of the vehicle. Third, most EVs have a shorter driving range relative to conventional vehicles and many consumers feel range anxiety; the limited number of charging stations and the rather long charging time (fastest charging time takes around 30 minutes) are cumbersome and inconvenient for many which further compounds the issue.

In order to overcome these barriers for market penetration, considerable attention and effort have been dedicated towards the research and development to improve the EV technology (Williander & Stålstad 2013). However, novel technologies do not possess a fixed inherent value and their market value is contingent upon the manner in which their commercialization is carried out (Chesbrough 2010). Commercialization takes place through *business models*, which describes how a company creates, delivers and captures value (Bohnsack et al. 2014). The most common business model for cars is full purchase – acquiring ownership of the car by paying the full purchase price. Some alternative business models for car adoption are vehicle leasing and battery leasing (only for battery electric vehicle). Pursuing the same technology in the market through different business models can yield different economic outcomes (Chesbrough 2010). Hence, it is hard to find out how much of the low sales of EV can be attributed to the technology itself and how much to the traditional business models (Wells 2013).

As we mentioned above, innovative sustainable technologies usually entail certain barriers for widespread market penetration, while current business models may be inadequate to address these barriers (Wells 2004). Therefore, applying prevailing business models is unlikely to achieve market success (Beaume & Midler 2009). Furthermore, innovative business models may be a prerequisite for sustainable technologies to become commercially viable and fulfill its potential in alleviating environmental problems (Budde Christensen et al. 2012).

If business models are found to be useful in increasing the market share of EVs, car manufacturers should pay more attention to providing innovative business models apart from focusing on improving EV technology; furthermore, the government should also dedicate some effort in stimulating business model innovation in addition to implementing financial purchase incentives and policies focusing on technical R&D (Birkin et al. 2007). Therefore, knowledge regarding consumer preferences in business models is of significant importance for the decision making of both car manufacturer marketing strategies and government EV promotion policies.

The preferences for business models are likely to be heterogeneous among the population. Apart from the common socio-economic variables, latent attitudes can also have important influence on preferences and choices. Attitudes depend on individuals' experience, values and lifestyles. Accounting for the impact of attitudes can both increase the explanatory power of the model and better characterize preference heterogeneity. Many previous studies on EV adoption have demonstrated the effects of latent attitudes such as pro-environmental (Daziano & Bolduc 2013), general technology perception (Kim et al. 2014) and attitudes towards leasing (Glerum et al. 2014). Given the above research gaps, our study aims to contribute to the literature by investigating consumer choices regarding both car type and business model. In particular, we explore to what extent attitudes play a role in these choices. In order to do this, we collect stated preference data and apply a state-of-the-art hybrid choice model, which considers these effects simultaneously. In this paper, we first briefly explain the concept of business model and some common examples of EV business models; next, we elaborate upon the conceptual model and its specification in section 3, which is followed by a description of survey design and data collection in section 4. Section 5 presents the model results and the final section concludes the paper.

3.2. Background: Business models

Based on existing theoretical frameworks, business models can be distinguished in terms of its three main components: (i) value proposition: the product/ service offered by the company; (ii) value network: the way in which the product/service is produced/provided regarding the stakeholders involved; (iii) revenue model: the type of payment used by the company to charge customers (Kley et al. 2011; Bohnsack et al. 2014). In our paper, we focus on value proposition and revenue model since they are most directly related to customers. In the classical business model currently adopted by conventional cars, the value proposition is the full ownership of the vehicle and the revenue model is one-time payment of full purchase price. This widely accepted model, however, constitutes some obstacles when it is applied in the case of EVs, which poses questions on its suitability. First, the “sell-and-disengage” model lets consumers deal with all the risks: this is acceptable for conventional cars with which car drivers are familiar, but less so for EVs, which are still new to most. Many potential consumers are concerned about the multiple risks surrounding EV including battery life, maintenance accessibility, rate of technology development, and residue value. Second, although the total cost of EV ownership throughout its lifetime may be around the same or is even lower than those for gasoline cars (Bubeck et al. 2016), the high purchase price which has to be paid at once creates a financial barrier for many potential customers. By adjusting one or more of the three main components, new business models can add additional value regarding efficiency and novelty by cost reduction and product differentiation respectively (Zott & Amit 2008).

In order to overcome key barriers, which are hindering EV market penetration and boost EV sales, many EV manufacturers have attempted adopting novel business models. They mainly made adjustments to the traditional business model in two ways: providing additional services by altering the value proposition or reducing initial purchase cost by changing revenue model (Kley et al. 2011). For a more exhaustive list of innovative business models for EV, see Bohnsack et al.(2014) and Kley et al. (2011).

In the academic literature, business models are mostly studied in the business and marketing field. There are also several studies regarding innovative business models for EV: Kley et al. (2011) utilized a holistic approach and identified the framework and building blocks for EV models which lays the foundation for future EV business model discussion. Wells (2013) provided a brief discussion of previous research regarding sustainable business models in the automotive industry and set an agenda for future research. Bohnsack et al. (2014) explored the impact of path dependencies of incumbents and startup firms in the EV industry on the evolution of their business models. However, most of these studies are either summaries of all potential business models or qualitative case studies focusing on a specific business model. Despite its wide application and high relevance with actual purchase choice in reality, insight in the impact of EV business models on EV adoption is still lacking.

To the best of our knowledge, the only studies on consumer preferences for EV which involved alternative business models are Glerum et al. (2014) and Valeri & Danielis (2015), both of which conducted a stated choice experiment including an EV alternative which has to be acquired via battery leasing. Glerum et al. also listed the leasing price of all alternatives and measured the attitude towards leasing. Despite the contribution of these studies, they share the main limitation that the impact of these business models is not disentangled from the effect of car brands and EV technologies. Therefore, the behavior change induced by providing new business models cannot be measured, making it difficult to draw conclusions regarding the potential of business models in increasing EV market penetration.

In this paper, we will focus on two of these new business models namely battery/vehicle *leasing* and mobility guarantee, since they do not require cooperation among various stakeholders (e.g. vehicle to grid) and drastic behavioral change of consumers (e.g. carsharing). Leasing is a business model in which consumers do not have the ownership of the car, nor do they pay the purchase price upfront. Instead, they have exclusive access to the car for a certain period of time (usually 3-4 years) by making a fixed monthly payment. In some countries (e.g. the Netherlands) this monthly rate also covers insurance cost, road tax and possible maintenance and repair costs. This model has already been applied to both conventional and electric vehicles. In the US, the penetration of leasing in EV market was over 75% in 2015, in contrast to 28% in the overall car market[13]. However, it is not clear whether this performance can be generalized for other regions where private leasing is less popular or under different settings (such as the Dutch leasing model). In case of full battery vehicles, it is also possible to purchase the car body and only lease the battery. By changing the revenue model of the dominating business model, both types of leasing reduce the financial burden of initial purchase cost and make EVs more affordable. They also alter the value proposition by providing extra service (maintenance and warranty for battery/car), which creates additional value for consumers. Furthermore, it shifts part of the risks from consumers to the car manufacturer and significantly reduces the uncertainties regarding the residue value of the car. However, it also implies that consumers are no longer car “owners” and they have to pay more eventually if they wish to obtain ownership, which they may perceive as a negative point.

Mobility guarantee is a value adding service targeting a specific barrier namely range anxiety: it provides a substitute conventional car for EV adopters for a certain number of days per year to cover their occasional long trips. Limited range is widely found as one of the main shortcomings of EV technology and a barrier for its wide adoption (Zubaryeva et al. 2012). However, studies of travel behavior reveal that many drivers’ current daily driving distance is well covered by the driving range of mainstream EVs, while the frequency of long trips which go beyond the EV range are rather low: if drivers can substitute a conventional vehicle for six days per year, electric vehicles with 160km range can already meet the range needs of 32% drivers in the US (Pearre et al. 2011). Therefore, changing the value proposition by providing a conventional car for these rare occasions may help to overcome this barrier.

[13] http://www.cnbc.com/2015/10/17/ric-cars.html

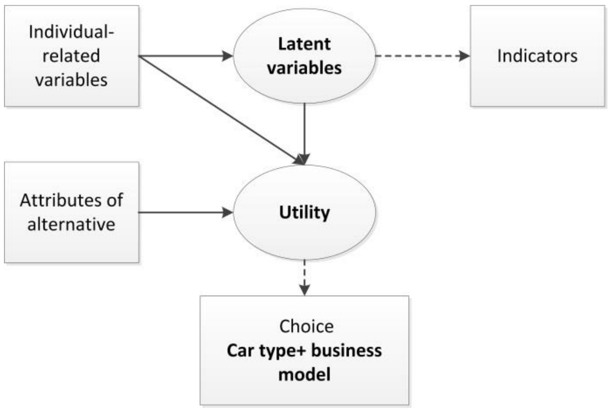

Figure 1. Conceptual model

3.3. Modeling framework

In order to investigate the impact of business models on consumer preferences, we adopt a disaggregated approach and apply discrete choice modeling to study consumer decision-making. In basic choice models, the utility of alternatives is mostly specified as a linear combination of attributes of alternatives and a set of taste parameters. In order to find out consumer preferences for business models, we conceptualize each alternative as a combination of car type and its business model. Therefore, each choice set consists of 7 available alternatives, namely "buy CV", "buy BEV", "buy PHEV", "lease battery of BEV", "lease CV", "lease BEV" and "lease PHEV". The preferences for these alternatives are expected to be heterogeneous and depend on the socio-economic and socio-demographic variables of individuals. Furthermore, as empirical evidences indicate, psychological constructs such as attitude and perception also have a significant impact on the utility of alternatives and hence the final choice (McFadden 1986). Therefore, we propose that attitudes towards business models affect consumer preferences as well. Attitudes can be measured by "indicators" which are responses to statements that describe an aspect of the attitude. Attitudes can also be partially explained by a series of individual-related variables, such as socio-demographics, etc. Figure 1 illustrates the conceptual model.

In order to study the impact of all factors in the consumer preference model, we applied a hybrid choice model. Ben-Akiva et al. (2002) proposed a hybrid choice model to enable the inclusion of latent variables (usually psychological constructs). It consists of two sub-models: a latent variable model and a discrete choice model. The latent variable model is essentially a Multiple Indicators MultIple Causes (MIMIC) model (Zellner 1970). It includes two components: a structural model describing the relationship between the latent variable and individual-related variables, and a measurement model, which specifies the relationship between the latent variable and the indicators.

The qth latent variable L^*_{nq} is assumed to be affected by a set of observable individual-related variables Z such as socio-economic characteristics. This is expressed as follows in the structural model:

$$L^*_{nq} = \gamma_{0q} + \sum_{z \in Z} \gamma_{qz} x_{nz} + \varepsilon_{nq}\ ,\ \ \varepsilon_{nq} \sim N(0, \sigma_{\varepsilon_q}) \tag{1}$$

where x_{nz} denotes individual-related variables of person n and ε_{nq} represents a disturbance term. γ_{0q}, γ_{qz} and σ_{ε_q} are parameters to be estimated.

The latent variable is identified by several indicators, which are usually responses to attitudinal statements on Likert scales. We assume the indicators are ordinal in measurement level and define the measurement model as follows:

$$z_{nd} = \lambda_{0d} + \lambda_d L^*_{nq} + \zeta_{nd}, \zeta_d \sim N(0, \sigma_{\zeta_d}) \tag{2}$$

$$I^*_{nd} = \begin{Bmatrix} j_1 & if\ z_{nd} < \tau_{q1} \\ j_2 & if\ \tau_{q1} \le z_{nd} < \tau_{q2} \\ & \vdots \\ j_i & if\ \tau_{qi-1} \le z_{nd} < \tau_{qi} \\ & \vdots \\ j_M & if\ \tau_{qM-1} \le z_{nd} < \tau_{qM} \end{Bmatrix} \tag{3}$$

z_{nd} is a continuous latent construct of the *d*th indicator of person *n* I^*_{nd}, in which λ_{0d}, λ_d and ζ_{nd} are parameters to be estimated. The probability of individual *n* choosing j_i as the response for indicator I^*_{nd} equals the cumulative probability of value z_{nd} lies within the range of τ_{qi-1} and τ_q.

If we are using a Likert scale with 5 levels, we only have to define two positive parameters instead of four considering the symmetry of indicators (Bierlaire 2016a):

$$\begin{aligned} \tau_{q1} &= -\delta_{q1} - \delta_{q2} \\ \tau_{q2} &= -\delta_{q1} \\ \tau_{q3} &= \delta_{q1} \\ \tau_{q4} &= \delta_{q1} + \delta_{q2} \end{aligned} \tag{4}$$

In the discrete choice model part, the utility function of alternative *j* in choice situation *t* for individual *n* is:

$$U_{jnt} = \boldsymbol{\beta}_X \boldsymbol{X}_{jnt} + \boldsymbol{\beta}_L \boldsymbol{L}^*_{nq} + ASC_j + \epsilon_n + \varepsilon_{jnt} \tag{5}$$

where $\boldsymbol{X}_{jnt}$ is a vector of vehicle attributes and $\boldsymbol{L}^*_{nq}$ is a vector of latent attitudes. $\boldsymbol{\beta}_X$and $\boldsymbol{\beta}_L$ are vectors of coefficients to be estimated. ASC_j is the alternative specific constant. For each vehicle type, there are two or three corresponding alternatives and each of which denotes a combination with a business model. Between these two or three alternatives we expect unobserved communalities. In order to capture these communalities, we added normally distributed error component ϵ_{BEV} and ϵ_{PHEV} apart from the i.i.d. error term ε_{jnt}. Since each respondent answered 6 choice tasks, we used a panel data structure to capture the correlation by using individual-specific error terms for ϵ_n. Therefore, the unconditional probability of the sequence of choices for individual *n* can be written as follows (Ben-Akiva et al. 2002):

$$P_n = \int_{\epsilon} \int_{L^*_n} \prod_t P_{jnt}\big(j|X, L^*_{n,}\epsilon_n\big) \prod_d P(I^*_{nd}|L^*_n, \lambda_{0d}, \lambda_{d,}\zeta_d) f(L^*_n|\gamma_z, x_{nz}, \varepsilon_{nq}) \;\; dL^*_n d\epsilon_n \tag{6}$$

in which the first term denotes the likelihood function of the choice model including latent variables, the second term represents the probability of indicators for a given respondent and the last term refers to the probability distribution of the latent variables.

We applied Pythonbiogeme (Bierlaire 2016b) for model estimation, 1000 Halton draws were used when simulation was required.

3.4. Data collection

We collected data in June 2016 via an online survey which included a stated choice experiment. The survey was developed on a platform of the Urban Planning Group in Eindhoven University of Technology. The respondents were recruited from a Dutch panel monitored by a marketing research company. Since our target is potential car buyers, the following criteria have to be met for a respondent to be selected in our sample: 1) have a driver's license, 2) own a car or expect to buy a car in the following three years, 3) the car cannot be second-hand or a company leasing car since in those cases private leasing is not applicable. Our final dataset consists of complete answers from 1003 individuals. The same dataset has also been used by Liao et al. (2018) in another study on the impact of business models on electric vehicle adoption. In this section we explain the most important features of the survey and choice experiment in this article. For a more detailed description and design considerations please refer to Liao et al. (2018).In the choice experiment, the respondents assume that they are choosing their next car. They have to make a choice between three versions of the same car: a conventional car powered by gasoline or diesel, a full battery electric vehicle and a plug-in hybrid electric vehicle. The generic attributes which apply for every alternative include purchase price, energy cost and driving range. There are several additional attributes for BEV such as fast charging station density, fast charging duration, policy incentives and mobility guarantee. In contrast to most studies, the PHEV alternative in our experiment has an additional attribute: the all-electric range, which is the range it covers when it is solely powered by battery. The experiment is tailor-made for each respondent to make the choice tasks more realistic: the value of purchase price and fuel cost of the conventional car alternative are based on the respondents' own answers earlier in the questionnaire (see below). Table 1 lists the selected attributes and the values of different levels.

Table 1. Selected attributes and their levels

Attribute	Alternative	Level 1	Level 2	Level 3
Purchase price	Conventional car (PPC)	Defined by respondent		
	BEV(euro)	0.8*PPC +5000	PPC + 5000	1.2*PPC+5000
	PHEV(euro)	0.8*PPC +5000	PPC + 5000	1.2*PPC+5000
Energy cost	Conventional car	Defined by respondent		
	BEV(euro/100km)	2	4	6
	PHEV(euro/100km)	2	4	6
All-electric range (AER)	PHEV(km)	30	70	110
Driving range	Conventional car (km)	600		
	BEV(km)	150	300	450
	PHEV(km)	600 + AER		
Fast charging station density	BEV(km) (highway/urban)	50/0	75/5	100/10
Fast charging duration	BEV(minutes)	10	20	30
Policy incentive	BEV	None	Road tax exemption	Free public parking
Mobility guarantee	BEV (days per year)	0	7	14

Source: Liao et al. 2018

Apart from the choice on car types, we also collected the choice on business models. Therefore, the respondents had to answer three questions for each choice task: they were first asked to choose an alternative when they have to pay the full purchase price. Next, the respondents were asked whether they would update their choice if battery leasing is available for BEV. The extra information given regarding the battery leasing model includes the car body price and monthly battery leasing cost for BEV. Finally, the respondents could make another choice assuming that they can now also lease any of the three cars. The monthly leasing payments of the three vehicles were shown to the respondents. All monthly payments for leasing were calculated based on the purchase price and also customized for each respondent depending on their annual mileage. In order for respondents to have some basic knowledge of the business models, the respondents were also shown an information page at the beginning of the experiment, which introduced the business model of battery leasing and vehicle leasing which includes an explanation of what the monthly payment covers.

The choice tasks were generated using a D-efficient optimal design by Ngene (ChoiceMetrics 2010). The priors for some taste parameters were taken from previous research findings (e.g. Hackbarth and Madlener, 2013; Hoen and Koetse, 2014). The final design consists of 12 choice tasks which were split into two blocks. Each respondent was randomly assigned to one of the blocks and had to complete 6 choice tasks. Figure 2 gives an example of the choice task[14].

Apart from the choice experiment, the online survey also included other information of the respondents including socio-demographics, current mobility pattern and the specifications of the next car they expect to purchase. Table 2 presented the descriptive statistics of the sample regarding their socio-demographics and basic characteristics of car ownership. Furthermore, we also measured respondents' attitudes towards leasing via ten attitudinal statements relevant for leasing. Each statement covers a possible aspect of motivation for preferring/disliking leasing, and is rated by a 5-point Likert scale ranging from ''completely disagree" to ''completely agree".

[14] In the questionnaire interface, the table of attributes (other than purchase price/lease payment) is shown throughout the entire choice task (for all three questions). For question 2 and 3, this figure only shows the questions and do not repeat the table of other attributes which is the same as in question 1. A full interface display of question 2 and 3 can be found in the appendix.

[Choice task 3 / 6 Question 1 / 3]

Assume you can choose from the following three cars:

Attributes	**Conventional vehicle**	**Battery electric vehicle (BEV)**	**Plug-in hybrid vehicle (PHEV)**
Fuel cost	€13 per 100 km	**€2** per 100 km	**€4** per 100 km
Driving range with full fuel tank/battery	600km	**450km**	Electric range: **30km** Total range: **630km**
Fast charging station density		**On highway: one station every 100 km** **In cities:** Within **10 minutes** ride from the often visited locations	
Fast charging duration(till 80% of battery capacity)		**20 minutes**	
Governmental **incentive policies**	None	**Free public parking**	None
Number of days per year that you can make additional use of conventional car	n.a.	**14 days** per year	n.a.

We now ask you **three questions** regarding the choice between **these three cars**.

1. Suppose you only have the option to **purchase** the cars described above. The prices Of these three cars are listed below. Which of these three cars would you buy?

Conventional vehicle	**Electric vehicle (BEV)**	**Plug-in hybrid vehicle (PHEV)**
€24000	**€33800**	**€29000**

(a) 1st question

Your previous choice: [X]	**[X]*Conventional vehicle*** €24000	**Battery electric vehicle** €33800	**Plug-in Hybrid vehicle** €29000

2. Now for **battery electric vehicle, you can choose to buy the car body only and lease the battery pack for a fixed payment per month. The price of the car body and the monthly leasing payment of the battery pack are listed below. Which car will you choose?**

Purchase	**Battery lease**
I keep my previous choice	**Battery electric vehicle** **€28800** **+€80 per month** **for maximum milage of 15.000km per year, 5 cent per extra km**

(b) 2nd question

Your previous choice: [X]	**Conventional vehicle** €24000	**[X] *Battery electric vehicle*** €28800 +€80 per month for maximum mileage of 15.000km per year, 5 cent per extra km	**Plug-in Hybrid vehicle (PHEV)** €29000

3. Suppose you can also **lease** one of the three cars. The **monthly lease fee** for these three cars are listed below. **Would you like to lease one of these three cars** Or will you keep your previous choice?

	Private lease for maximum mileage of **15.000km** per year, **10 cent** per extra km		
I keep my previous choice	**Conventional vehicle** **€377 per month**	**Battery electric vehicle** **€533 per month**	**Plug-in Hybrid vehicle (PHEV)** **€473 per month**

(c) 3rd question

Figure 2. Example of choice task (translated from Dutch)

Source: Liao et al. 2018

Table 2. Sample Characteristics

Items		Value	Percentage
Socio-Demographics	Gender	Male	51.7
		Female	48.3
	Age	<=35 years	25.0
		36-50 years	24.0
		51-65 years	30.8
		>=66 years	19.2
	Number of household Members	1 person	16.8
		2 person	44.3
		3 person	16.7
		>=4 person	22.2
	Education level	No high education	56.6
		With high education*	43.4
	Monthly net personal income (euro)	<625	6.8
		625-1250	10.6
		1251-1875	18.9
		1876-2500	30.3
		2501-3125	17.9
		>3125	15.5
Information regarding car ownership and the expected car	Number of cars	0	1.0
		1	68.4
		2	27.6
		More than 2	3.0
	Purchase cost of expected car (1000 euro)	10-15:	38.7
		16-20:	24.2
		20-30:	24.6
		>30:	12.5
	Fuel type of expected car	Gasoline	77.3
		Diesel	9.9
		LPG	1.6
		Hybrid	4.7
		BEV	2.6
		PHEV	2.4
		Others	1.6

Note: *: Those who received higher vocational or university education.
Source: Liao et al. 2018

3.5. Results

This section first presents the result of a multinomial logit model which reveals consumer preferences for business models in case of different car types; next we elaborate the results of the hybrid choice model which show the effects of attitudes on consumer preferences. Both choice models are estimated based on only the final choice of respondents in each choice task, since in this study we only focus on the preference when all business models are available.

3.5.1 Consumer preference for business models

3.5.1.1 Model results

We would like to first find out which business model is the most preferred for each car type. Apart from the basic multinomial logit model, we also estimated an error components mixed logit model which adopted the error component structure explained in section 3. Table 3 shows the results of both models. In both the MNL and mixed logit model, alternatives with the same car type have utility functions of identical form; therefore, their alternative specific constants

can be directly compared to identify consumer preferences for business models. From Table 3 we can see that for BEV vehicle lease is the favorite option and battery leasing is the least popular option. For a person who intends to purchase a 15,000-euro car, the willingness to pay for leasing a BEV is 1213 euro higher than buying a BEV according to the result of the error components model. For CV and PHEV it is the opposite: buying has a higher ASC in contrast to leasing (ASC for buying CV is set to 0) thus is the preferred option. This result shows that the value of leasing is different depending on the car type.
As for mobility guarantee, its impact on BEV utility is insignificant, which implies that this service does not play an important role when consumers making the choice of car type.

Table 3. Results of multinomial logit model and mixed logit model

		Multinomial logit model			Mixed logit model		
Parameters		**Estimate**	**Standard error**	**p-value**	**Estimate**	**Standard error**	**p-value**
Alternative specific constants							
BEV	Buy	-1.60	0.208	0.00	-3.91	0.347	0.00
	Battery lease	-2.22	0.213	0.00	-4.53	0.351	0.00
	Lease	-1.31	0.206	0.00	-3.62	0.347	0.00
	Standard deviation				4.32	0.212	0.00
PHEV	Buy	-1.32	0.104	0.00	-3.16	0.244	0.00
	Lease	-2.08	0.112	0.00	-3.91	0.247	0.00
	Standard deviation				3.98	0.198	0.00
CV	Lease	-0.964	0.0359	0.00	-0.964	0.0359	0.00
Attributes							
Relative purchase price	All	-0.127	0.00647	0.00	-0.239	0.0111	0.00
Energy cost	All	-0.111	0.0147	0.00	-0.174	0.0206	0.00
Driving range	BEV	0.0537	0.0301	0.07	0.105	0.0435	0.02
All-electric range	PHEV	0.265	0.106	0.01	0.671	0.159	0.00
Fast charging availability	BEV	-0.258	0.176	0.14	-0.228	0.252	0.37
Fast charging duration	BEV	0.0120	0.255	0.96	-0.00185	0.379	1.00
Road tax exemption	BEV	0.0843	0.0490	0.09	0.161	0.0697	0.02
Free public parking	BEV	0.0226	0.0519	0.66	-0.105	0.0761	0.17
Mobility guarantee	BEV	0.00928	0.0414	0.82	0.0129	0.06	0.83
Number of observations	6014						
Null-Likelihood	-11702.704						
Final likelihood		-9199.079			-7778.477		
Rho-squared		0.214			0.335		

3.5.1.2 Application of the models: EV adoption under four policy scenarios

The results above imply that implementing financial incentives in case of leasing can also increase EV adoption. In order to illustrate the impact of the combination of financial incentive and leasing, we simulated the market share of the three car types under different policy scenarios. Table 4 lists the values of all vehicle attributes in the base scenario. The distribution of expected car price is based on our sample. The taste parameters are taken from the mixed logit model in Table 3. We calculated the choice probabilities for each alternative first on an individual level and then take the average. In order to calculate the confidence intervals, we take 100 draws for the taste parameters and for each draw of taste parameters 100 draws are taken for the random error components; therefore, in total we use 10,000 draws for each individual. Table 5 shows the market share of the three car types and their confidence intervals under the five different policy scenarios (including the base scenario without any policy incentives). The first policy scenario is a financial incentive which reduces the purchase price of BEV to only 5000 euro more than the expected car price only when consumers are buying:

intuitively the market share of BEV increases to 16.9% compared to 14.0% in the base scenario; the share of PHEV slightly decreases but the share of EV in general (BEV and PHEV) climbs from 24.3% to 26.6%. When the financial incentive is also applied to leasing (new lease BEVs are only 5000 euro more expensive than the expected car price), the market share of BEV is further increased to 20.3%. In scenario 3 when this financial incentive is implemented on both BEV and PHEV but only when buying (not leasing), the market share for EV reaches 29.5% which is the highest compared to the previous two policies; however, most of the growth comes from PHEV while the share of BEV is even lower than when the incentive is applied to BEV buying only (15.7% vs 16.9%). From a policy perspective, implementing the incentive on BEV leasing instead of PHEV buying could be an attractive option since BEVs are zero emission vehicles and can have larger environmental benefits compared to PHEVs. Lastly, if the incentive is applied to both BEV and PHEV under all business models, the market shares of both types of EV are higher than in scenario 3, but the share of BEV is still lower than in scenario 2. Note that the costs of the policies also need to be considered in real world policy decisions.

Table 4. Parameter values of basic scenario

Parameter	Value
CV purchase price	Expected car price
BEV purchase price	1.2* expected car price +5000 euro
PHEV purchase price	1.2* expected car price +5000 euro
BEV energy cost	4 euro/100km
PHEV energy cost	6 euro/100km
BEV driving range	200 km
PHEV all-electric range	50 km
BEV fast charging duration	30 minutes
BEV fast charging station density	50 km on highway
BEV policy incentive	None
BEV mobility guarantee	None

Table 5. Simulation results of different policy scenarios

Scenario	CV market share (%)	BEV market share (%)	PHEV market share (%)	EV market share (%)
0: Base scenario	75.7 (72.1-79.6)	14.0 (11.7-16.6)	10.3 (8.8-12.2)	24.3 (20.5-28.7)
1: Reduction of BEV purchase price	73.4 (70.0-77.1)	16.9 (14.1-19.9)	9.7 (8.5-11.3)	26.6 (22.5-31.2)
2: Reduction of BEV purchase price and leasing payment	70.7 (67.1-74.5)	20.3 (17.3-23.8)	9.0 (7.8-10.6)	29.3 (25.1-34.4)
3: Reduction of EV purchase price	70.5 (67.0-74.3)	15.7 (13.2-18.7)	13.8 (12.1-15.6)	29.5 (25.2-34.3)
4: Reduction of EV purchase price and leasing payment	67.2 (63.8-70.8)	18.7 (15.7-21.9)	14.1 (12.2-16.1)	32.8 (28.0-38.1)

Note: the 90% confidence interval of each market share is shown in the bracket below.

3.5.2 Preference heterogeneity: the effect of socio-economic variables and attitudes

3.5.2.1 Attitude towards leasing

The online survey included ten attitudinal statements related to leasing, each statement describing a possible motivation or reason for preferring/disliking leasing. A 5-point Likert scale was used for rating, namely ‘‘completely disagree”, ‘‘disagree’,’ ‘‘neutral’, ‘‘agree’’, and ‘‘completely agree”. Table 6 lists the statements, the mean and standard deviation of their scores and the parameter estimates in the measurement model.

First, we conducted an exploratory factor analysis to extract factors and derive three factors as shown in Table 6. Scoring high on the factor of pro-convenience implies that someone finds leasing to be beneficial because it saves trouble and reduces risk. A high score on the pro-ownership factor means car ownership is preferred to leasing in multiple aspects of consideration. The last factor Pro EV leasing stands for the view that leasing is more suitable for EV than for conventional vehicles. From the scores we can see that in general many people can recognize and appreciate the convenience brought by private leasing, but the vast majority are more or less emotionally attached to owning a vehicle and do not like the idea of leasing. As for the suitability of leasing for EV, the close to neutral average score and the relatively small standard deviation suggests that many people may not have sufficient knowledge to hold an opinion.

Table 6 also presents the measurement relationships between indicators and latent attitudes. The parameters of the first indicator are fixed so the other parameters in the measurement model can be identified. Therefore, the estimated effects of other indicators are relative. All indicators are positively and significantly related to their corresponding latent attitudes (see λ_d), which shows that people with a higher score of a latent attitude are more likely to agree with the corresponding statements.

Table 6. Statements, scores and measurement model

Statements	Average	Standard deviation	λ_d	λ_{0d}	σ_{ζ_d}	δ_1	δ_2
Factor 1 Pro-convenience							
Leasing is nice because I can switch cars regularly.	2.78	1.030	1	0	0	0.582 (0.0182)	0.896 (0.0287)
Leasing is nice because the risks of maintenance and damage are not for me.	3.33	0.928	0.645 (0.110)	0.502 (0.0467)	0.898 (0.0339)		
Leasing is nice because I know exactly how much I have to pay every month.	3.34	0.913	0.693 (0.112)	0.523 (0.0474)	0.874 (0.033)		
I find it important that a lot of hassle is gone when leasing a car.	3.12	0.931	0.794 (0.118)	0.313 (0.0487)	0.887 (0.0333)		
Factor 2 Pro-ownership							
I prefer to pay the total price at one time than paying each month.	3.73	0.977	1	0	0	0.497 (0.0178)	1.000 (0.0318)
I prefer to own a car than to lease one.	3.89	0.917	1.17 (0.233)	0.0457* (0.185)	0.942 (0.0388)		
Car lease is more suitable for company cars than for private cars.	3.55	0.967	0.906 (0.206)	-0.134* (0.164)	0.951 (0.0376)		
I do not want to lease a car because it is more expensive than buying a car.	3.49	0.950	0.635 (0.178)	0.0147* (0.142)	0.941 (0.0372)		
Factor 3 Pro EV leasing							
Leasing contract is more suitable for EV than for conventional cars.	2.9	0.849	1	0	0	0.817 (0.0244)	0.858 (0.035)
EV batteries are better to be leased than purchased.	3.14	0.758	0.825 (0.236)	0.286 (0.0502)	0.890 (0.0321)		

Note: 1) The standard errors of each estimated coefficient are in the parenthesis below.
2) All estimates are statistically significant apart from the ones marked with asterisk.

Table 7 shows the estimation results for the structural model of the three latent variables. Several socio-demographic and socio-economic variables are significantly associated with these latent attitudes. The results reveal that people who are younger than 40, employed or student or have young children appreciate the convenience of leasing more. However, those who are retired, have higher income or own more than one car tend to recognize the convenience of car lease to a lesser extent in contrast to others. As for the attitude towards car ownership, males, parents with young kids, workers and students are less attached to car ownership. On the other hand, people with high degrees appreciate car ownership more than those who do not. Regarding the suitability of leasing for EV, people younger than 40 are more likely to agree that leasing is more suitable for EV than conventional cars, while those with more than one car agree to a lesser extent. Of all tested individual-specific variables, gender, number of household members and the presence of teenage children have no significant effect on any of the latent attitude variables.

Table 7. Structural model of latent variables

Latent variable	Parameter	Estimate	Std. error	p-value
Pro-convenience	Intercept	**-0.387**	0.0741	0.00
	Male	0.0446	0.0417	0.28
	Younger than 40	**0.128**	0.0518	0.01
	Number of household members	0.00293	0.00623	0.64
	Presence of young children (4-12 years)	**0.233**	0.0639	0.00
	Presence of teenage children (13-17 years)	-0.00672	0.0669	0.92
	High income (>3125 euro)	**-0.199**	0.0629	0.00
	High education (University)	0.00408	0.0445	0.93
	Employed	**0.141**	0.0693	0.04
	Retired	*-0.144*	0.0799	0.07
	Student	**0.278**	0.129	0.03
	Have more than one car	**-0.128**	0.0468	0.01
	Standard deviation σ_{ε_1}	**0.258**	0.0291	0.00
Pro-ownership	Intercept	**0.848**	0.0679	0.00
	Male	-0.0414	0.0361	0.25
	Younger than 40	0.0684	0.0446	0.12
	Number of household members	-0.000961	0.00537	0.86
	Presence of young children (4-12 years)	**-0.186**	0.0559	0.00
	Presence of teenage children (13-17 years)	0.0274	0.0577	0.63
	High income (>3125 euro)	0.0804	0.0548	0.14
	High education (University)	**0.0834**	0.0395	0.03
	Employed	**-0.135**	0.0612	0.03
	Retired	0.0996	0.0711	0.16
	Student	**-0.289**	0.116	0.01
	Have more than one car	0.0218	0.0395	0.58
	Standard deviation σ_{ε_2}	**-0.167**	0.0292	0.00
Pro EV leasing	Intercept	**-0.287**	0.0915	0.00
	Male	0.0605	0.0540	0.26
	Younger than 40	**0.230**	0.0693	0.00
	Number of household members	-0.00444	0.00802	0.58
	Presence of young children (4-12 years)	0.0903	0.0788	0.25
	Presence of teenage children (13-17 years)	0.0809	0.0863	0.35
	High income (>3125 euro)	0.0193	0.0758	0.80
	High education (University)	-0.000758	0.0560	0.99
	Employed	0.104	0.0884	0.24
	Retired	0.0353	0.101	0.73
	Student	0.0574	0.171	0.74
	Have more than one car	**-0.153**	0.0654	0.02
	Standard deviation σ_{ε_3}	**0.123**	0.0278	0.00

3.5.2.2 Choice model

Table 8 presents the estimation results of the discrete choice model part of the hybrid choice model. Almost all effects of latent attitudes on business model preferences are statistically significant. The results show that pro-convenience is found to be positively associated with the leasing option of all three car types. The effect is especially strong for BEV vehicle leasing, which shows that the additional convenience brought by leasing is an important consideration especially for BEV. The effect of pro-ownership is negative for all four alternatives with alternative business models as expected. The size of the effect differs widely for different business models and car types. The effect is the smallest for battery leasing, which is intuitive since the individual who chooses battery leasing still owns the car body. The magnitude of this effect is especially large for BEV and PHEV: this indicates that for a person valuing ownership relatively high, the aversion towards leasing an EV is stronger than towards a CV. As for the attitude of pro EV leasing, it has a significant positive impact on both battery leasing and vehicle leasing for BEV, which is an intuitive result; and the effect is stronger for battery leasing than vehicle leasing, which implies that the difference between the utility of battery leasing and vehicle leasing is smaller for a person who is more pro- EV leasing than average when all else being equal. On the other hand, pro-EV leasing does not seem to have an impact on PHEV lease, which suggests that PHEV may have a vastly different image and concept in consumers' mind in contrast to BEV.

We included interaction items of socio-economic variables with ASCs to investigate their effect on the general preference for each alternative. Since we also incorporated latent attitudes in the utility function of alternatives with leasing, these socio-economic variables can affect the utility both directly on ASC and indirectly via latent attitudes. We can deduce the combined effects from the results of both the structural latent variable model and the choice model. For example, people who have young children prefer to buy BEV and PHEV (0.646 and 0.369). As for the effect of young children's presence on the utility of leasing BEV, it can be calculated as -2.19 (direct) +8.76*0.233 (indirect via pro-convenience) + (-16.5) * (-0.186) (indirect via pro-ownership) = 2.92; therefore, it has a positive net impact. In fact, people who have young children have a higher preference for all four alternatives associated with (battery or vehicle) leasing. Many other socio-economic variables also have a significant net impact on the utility of the alternatives:

- Younger people (less than 40 years old) also have higher preference for all four leasing alternatives; the variable "young" also has a positive impact on buying BEV alternative but not PHEV.
- Higher income earners have lower preference for buying BEV and PHEV and are also less interested in battery leasing, but they prefer leasing CV and PHEV.
- Those who are highly educated prefer buying BEV and PHEV and are also more interested in vehicle leasing in terms of all three car types than those with less education, while they have less preferences for battery leasing.
- As for the influence of occupation, students have the highest preference for buying BEV and PHEV while retired people's preference are the lowest; however, concerning the preference for leasing, students still have the highest interest while those employed are the least interested. This is likely due to the fact that many employees lease car via a company deal but we excluded these people from our sample.
- Having more than one car in the household also contributes positively to the utility of buying both types of EVs and all four leasing alternatives.
- Gender, number of household members and the presence of teenage children do not have any significant direct nor indirect effect on utilities.

Table 8. Discrete choice model part of the hybrid choice model

Parameters		Estimate	Standard error	p-value
Alternative specific constants and standard deviation				
BEV	Buy	-1.91	0.318	0.00
	Lease battery	2.25	1.63	0.17
	Lease	10.9	3.15	0.00
	Standard deviation	0.781	0.102	0.00
PHEV	Buy	-1.53	0.187	0.00
	Lease	9.34	2.92	0.00
	Standard deviation	0.584	0.0865	0.00
CV	Lease	9.87	2.20	0.00
Attitudes				
Pro convenience	Lease CV	9.06	1.22	0.00
	Lease BEV	8.76	2.64	0.00
	Lease PHEV	11.8	1.79	0.00
Pro ownership	Battery lease BEV	-6.79	1.79	0.00
	Lease CV	-12.9	2.43	0.00
	Lease BEV	-16.5	3.71	0.00
	Lease PHEV	-16.1	3.47	0.00
Pro EV leasing	Battery lease BEV	6.02	1.82	0.00
	Lease BEV	9.24	4.59	0.04
	Lease PHEV	0.863	1.49	0.56
Socio-economic variables				
Male	Buy BEV	-0.273	0.124	0.03
	Buy PHEV	-0.0628	0.0989	0.53
	Battery lease BEV	0.296	0.438	0.50
	Lease CV	0.0554	0.602	0.93
	Lease BEV	-0.133	0.881	0.88
	Lease PHEV	0.0283	0.774	0.97
Younger than 40	Buy BEV	0.3	0.148	0.04
	Buy PHEV	0.0415	0.124	0.74
	Battery lease BEV	-0.352	0.656	0.59
	Lease CV	0.594	0.737	0.42
	Lease BEV	-0.558	1.35	0.68
	Lease PHEV	-0.0632	1.04	0.95
Number of household members	Buy BEV	-0.0509	0.0599	0.40
	Buy PHEV	-0.0228	0.0267	0.39
	Battery lease BEV	0.00926	0.0689	0.89
	Lease CV	-0.0291	0.0904	0.75
	Lease BEV	0.0166	0.132	0.90
	Lease PHEV	-0.0831	0.136	0.54
Presence of young children	Buy BEV	0.646	0.20	0.00
	Buy PHEV	0.369	0.16	0.02
	Battery lease BEV	-0.368	0.657	0.58
	Lease CV	-1.68	0.911	0.07
	Lease BEV	-2.19	1.30	0.09
	Lease PHEV	-2.03	1.18	0.08
Presence of teenage children	Buy BEV	0.0456	0.215	0.83
	Buy PHEV	-0.253	0.173	0.14
	Battery lease BEV	0.284	0.701	0.69
	Lease CV	0.568	0.965	0.56
	Lease BEV	0.514	1.43	0.72
	Lease PHEV	1.32	1.24	0.29
High income	Buy BEV	-0.735	0.194	0.00
	Buy PHEV	-0.356	0.142	0.01
	Battery lease BEV	-0.471	0.636	0.46
	Lease CV	2.00	0.905	0.03
	Lease BEV	1.65	1.37	0.23
	Lease PHEV	2.58	1.17	0.03
High education	Buy BEV	0.715	0.128	0.00
	Buy PHEV	0.606	0.103	0.00
	Battery lease BEV	0.654	0.476	0.17
	Lease CV	1.33	0.66	0.04
	Lease BEV	2.40	0.957	0.01
	Lease PHEV	2.23	0.86	0.01

Employed	Buy BEV	0.211	0.191	0.27
	Buy PHEV	0.0269	0.152	0.86
	Battery lease BEV	0.196	0.827	0.81
	Lease CV	-2.26	1.03	0.03
	Lease BEV	-3.37	1.49	0.02
	Lease PHEV	-2.46	1.34	0.07
Retired	Buy BEV	-0.487	0.236	0.04
	Buy PHEV	-0.201	0.175	0.25
	Battery lease BEV	1.82	0.909	0.05
	Lease CV	2.27	1.19	0.06
	Lease BEV	2.92	1.76	0.10
	Lease PHEV	3.93	1.56	0.01
Student	Buy BEV	1.00	0.345	0.00
	Buy PHEV	0.434	0.304	0.15
	Battery lease BEV	0.393	1.43	0.78
	Lease CV	-4.51	1.92	0.02
	Lease BEV	-5.35	2.79	0.06
	Lease PHEV	-3.9	2.48	0.12
Have more than one car	Buy BEV	0.125	0.136	0.36
	Buy PHEV	0.453	0.106	0.00
	Battery lease BEV	1.51	0.552	0.01
	Lease CV	1.62	0.679	0.02
	Lease BEV	3.01	1.09	0.01
	Lease PHEV	2.38	0.892	0.01
Attributes				
Relative purchase price	All	-0.138	0.00722	0.00
Energy cost	All	-0.113	0.0160	0.00
Driving range	BEV	0.0664	0.0335	0.05
All-electric range	PHEV	0.21	0.112	0.06
Fast charging availability	BEV	-0.245	0.198	0.22
Fast charging duration	BEV	-0.0746	0.286	0.79
Road tax exemption	BEV	0.103	0.0554	0.06
Free public parking	BEV	-0.0279	0.0581	0.63
Mobility guarantee	BEV	0.00759	0.047	0.87
Number of observations		6014		
Choice model Log-likelihood		-8101		
Rho-squared		0.308		
Full model null Log-likelihood		-38307		
Final Log-likelihood		-20845		
Rho-squared		0.456		

As for the estimated parameters of other vehicle attributes, most are significant and have the expected sign. Purchase price and fuel cost both have a negative effect on the probability of a car being chosen. Driving range of BEV has a positive impact on its utility. A point worth noticing is that consumers strongly prefer PHEVs with longer electric range. As for the fast charging station density and charging duration, neither of them is significant. This can be due to the following reasons: 1) consumers are genuinely indifferent for these two attributes as long as their value fall in between the range given in the choice experiment; 2) only a small group of people consider BEVs and have a clear preference for these two attributes: this effect may become insignificant on average in the entire sample. Regarding the two incentive policies, road tax exemption seems to have a positive impact on the attractiveness of BEV while the effect of free public parking is insignificant.

3.6. Conclusions and discussions

In order to facilitate a higher market penetration of EVs, most efforts have been focused on technological improvement while the potential of business model in promoting EV sales is often ignored in both the academic literature and public policy making. The present study contributes to the literature by examining consumer preferences for different business models regarding the decision of EV adoption; in particular, we investigated how these preferences can be affected by their latent attitudes. This knowledge can serve as valuable input for making EV promotion policies and strategies. We collected stated preference data and responses to attitudinal statements related to leasing from potential consumers. In order to simultaneously assess the impact of vehicle attributes and consumers' latent attitudes, we estimated a hybrid choice model to analyze the data.

Our results show that for BEV, vehicle leasing is the most popular option while battery leasing is less preferred than full price purchase. However, the preference for business models is exactly the opposite for CV and PHEV: the traditional full price purchase is preferred to vehicle leasing. This provides several interesting insights: first, it shows that providing vehicle leasing indeed has added value for BEV, while battery leasing is the least favorite business model on average, which implies that it may only be appealing for a rather small group; second, the impact of vehicle leasing varies for different car types: in contrast to BEV, people would still rather stick to one-time purchase instead of leasing with a monthly payment when adopting CV and PHEV. Furthermore, providing mobility guarantee for up to 2 weeks per year does not significantly increase the attractiveness of BEV, which indicates that it does not play an important role in decision-making when being juxtaposed with the other attributes in the choice experiment.

As for the impact of latent variables on business model preferences, almost all effects tested are statistically significant. Higher appreciation for the convenience of leasing leads to higher probability of choosing vehicle leasing for all three car types, which implies that apart from the reduced financial burden of paying full price in one go, the increased convenience is also taken into account when choosing vehicle leasing. On the other hand, people who appreciate car ownership are less likely to choose leasing. Moreover, those who believe that EVs are more suitable for leasing than conventional vehicles are more likely to adopt BEV via battery and vehicle leasing, while it does not have a significant impact on the probability of leasing PHEV.

Some implications for policy making and marketing strategies can be derived from our results. First, for both types of EVs, the implementation of financial incentive in the leasing business model can further increase their market shares than when they are only applied in buying. Given this insight, governments can extend their existing or planned incentives for EV purchase and make them also applicable for leasing; they can also offer some extra incentives to reduce the cost of implementing this business model. A point worth noticing is that subsidizing PHEV can reduce the market share of BEV; therefore governments shall choose the combination of applicable car types and business models depending on their goals (e.g. whether to promote all EVs or only those with zero-emission such as BEV). Second, in the case of BEV, vehicle leasing is significantly preferred to buying which implies that vehicle leasing has added value for BEV adopters. In order to ensure that potential BEV adopters are aware of and can benefit from it, car manufacturers can work on familiarizing potential BEV adopters with leasing and providing easy access to leasing which reduce the transaction cost of this business model, including offering customized advice regarding the selection of lease company/plan and simplifying the procedure of leasing, etc. However, our model also shows that the relative consumer preference for leasing and buying are reversed for BEV and PHEV, and the impact of pro-EV leasing attitude also differs for BEV and PHEV vehicle leasing. These results seem to suggest that consumers regard these two types of EV differently and these two should not be mixed up when discussing and making promotion policies and strategies regarding EV and leasing. Third, as we elaborated above, consumer preferences for business models are found to be highly heterogeneous and significantly influenced by people's individual-specific variables; therefore, it gives guidance for identifying those people who are more likely to choose leasing. Furthermore, informational campaigns on leasing and policies/ marketing strategies which facilitate leasing shall ideally be tailor-made for target population according to their characteristics. For example, people's attitudes have a significant impact on their preferences for leasing, which sheds some light into the possible motivations for people's interest (or lack of interest) for leasing. Having this knowledge, information campaigns/ promotions for leasing shall take all these motivations (higher convenience/ less financial burden) into consideration. The relation between attitudes and socio-economic variables with preferences also provide insights helpful for identifying potential customers' which have strong interest for leasing and EVs, which can eventually fulfill the potential of business models in facilitating more EV adoption.

This research also has some limitations: first, it only included a fixed price level (a fixed percentage of the purchase price) for each battery leasing and vehicle leasing option, which made it impossible to investigate the effect of pricing scheme on the popularity of business models. Also, the highest level of mobility guarantee tested is only 14 days, which may still be insufficient for some people. Second, the context of the choice experiment is to choose from three different powertrain versions of the same car model and leasing is available for all three versions, which is an over-simplified version of the real world. It may be also interesting to explore how the consideration of business model trade-off with car types, brands and models when business models are not provided for all cars.

We also recommend several directions for future research regarding the impact of business models on consumer preferences for electric vehicles and other sustainable technologies: first, latent class models can be applied to systematically characterize and explain the origin of the heterogeneity underlying consumer preferences for business models. Second, the current model in our study can be further extended to incorporate more potential influential factors and relationships, such as the interaction between latent attitudes and vehicle attributes, etc. Some attribute coefficients can also be made specific for different business models, since attributes such as purchase price, fuel cost and fast charging availability may be valued differently under the contexts of buying and leasing. These extensions can provide more nuanced and in-depth understanding of people's preferences and behavior. Third, explore the potential of more types of business models which may be suitable for promoting innovative technologies and in particular EV, such as carsharing, vehicle-to-grid, etc. Finally, apart from consumers' preference for business models when they adopt a car, a more intriguing question under our specific context (EV adoption) is whether the provision of alternative business models can facilitate more EV sales and increase the market share; in other words, can business models shift consumers who previously would have bought conventional vehicles into EV adopters? The answer to this question is more relevant for public policy making since it helps to reach the goal of EV promotion and reducing the sustainability impact of road transport.

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Appendix: Example of the full display of the 2nd and 3rd questions of a choice task (translated from Dutch)

Assume you can choose from the following three cars:

Attributes	Conventional vehicle	Battery electric vehicle (BEV)	Plug-in hybrid vehicle (PHEV)
Fuel cost	€13 per 100 km	**€2** per 100 km	**€4** per 100 km
Driving range with full fuel tank/battery	600km	**450km**	Electric range: **30km** Total range: **630km**
Fast charging station density		**On highway: one station every 100 km** **In cities:** Within **10 minutes** ride from the often visited locations	
Fast charging duration(till 80% of battery capacity)		**20 minutes**	
Governmental **incentive policies**	None	**Free public parking**	None
Number of days per year that you can make additional use of conventional car	n.a.	**14 days** per year	n.a.
Your previous choice: [X]	[X]*Conventional vehicle* €24000	**Battery electric vehicle** €33800	**Plug-in Hybrid vehicle** €29000

2. Now for **battery electric vehicle, you can choose to buy the car body only and lease the battery pack for a fixed payment per month. The price of the car body and the monthly leasing payment of the battery pack are listed below. Which car will you choose?**

Purchase	Battery lease
I keep my previous choice	**Battery electric vehicle** **€28800** **+€80 per month** **for maximum milage of 15.000km per year, 5 cent per extra km**
○	○

a) Second question

Assume you can choose from the following three cars:

Attributes	Conventional vehicle	Battery electric vehicle (BEV)	Plug-in hybrid vehicle (PHEV)
Fuel cost	€13 per 100 km	**€2** per 100 km	**€4** per 100 km
Driving range with full fuel tank/battery	600km	**450km**	Electric range: **30km** Total range: **630km**
Fast charging station density		**On highway: one station every 100 km** **In cities:** Within **10 minutes** ride from the often visited locations	
Fast charging duration(till 80% of battery capacity)		**20 minutes**	
Governmental **incentive policies**	None	**Free public parking**	None
Number of days per year that you can make additional use of conventional car	n.a.	**14 days** per year	n.a.
Your previous choice: [X]	**Conventional vehicle** €24000	[X] *Battery electric vehicle* €28800 +€80 per month for maximum mileage of 15.000km per year, 5 cent per extra km	**Plug-in Hybrid vehicle (PHEV)** €29000

3. Suppose you can also **lease** one of the three cars. The **monthly lease fee** for these three cars are listed below. **Would you like to lease one of these three cars** Or will you keep your previous choice?

	Private lease for maximum mileage of **15.000km** per year, **10 cent** per extra km		
I keep my previous choice	**Conventional vehicle** **€377 per month**	**Battery electric vehicle** **€533 per month**	**Plug-in Hybrid vehicle (PHEV)** **€473 per month**
○	○	○	○

b) Third question

4. The impact of business models on electric vehicle adoption: a latent transition analysis approach

Liao, F., Molin, E., Timmermans, H., & van Wee, B. (2018). The impact of business models on electric vehicle adoption: A latent transition analysis approach. Transportation Research Part A: Policy and Practice, 116, 531–546. https://doi.org/10.1016/j.tra.2018.07.008

Abstract

It is often argued that successful market penetration of electric vehicles may not only rely on the characteristics of the technology but also on business models. However, empirical evidence for this is largely lacking. This study intends to fill this gap by assessing the impact of business models, in particular battery and vehicle leasing, on Electric Vehicle (EV) adoption. By conducting a stated choice experiment, we examine to what extent car drivers switch their choices between conventional and electric vehicles after business models become available. The results based on the discrete choice model suggest that leasing does not increase EV adoption at the aggregate level. However, a latent transition analysis shows that different groups with internally homogeneous preferences react differently to leasing options at the disaggregate level. The results indicate that 13% of the car drivers changed their preferences, albeit in different ways. Transition probabilities are particularly related to attitudes towards leasing and knowledge of EV. The results show that leasing is useful in facilitating EV adoption for certain groups, which can be identified by their individual characteristics. In addition to these substantial insights, this paper makes a contribution to the literature by demonstrating the potential of latent transition analysis in uncovering heterogeneity in behavioral changes induced by policy or strategy interventions, especially when changes can occur in opposite directions.

4.1 Introduction

Substituting fossil-fueled cars by electric vehicles is considered to be a potential solution for many problems caused by road transport, including excessive CO_2 emission, environmental pollution and oil dependency. However, its market penetration has not been quite smooth except for only a few countries (e.g. Norway). Many researchers blame this on several deficiencies of EV in contrast to gasoline vehicles, such as expensive price and high uncertainties regarding battery upgrade and life expectancy. In order to reduce these barriers, most attention has been paid to improve the quality and reduce production cost through intensive Research & Development of EV (mainly battery) technology (Williander and Stålstad, 2013). However, an option often ignored in the literature is the implementation of different business models for commercialization of EV.

A business model has three key components: (i) value proposition: the product or service provided by the company; (ii) value network: the way in which the involved stakeholders are organized; and (iii) revenue model: the way in which the company to charge customers (Bohnsack et al., 2014; Kley et al., 2011). An example of business model is leasing. Consumers who lease a car do not have to pay the full purchase price upfront, which may help overcome the higher purchase costs of EV. Instead, they pay a fixed monthly leasing rate and have exclusive access to the car for around 3 to 4 years. At the end of this period, they can pay a surcharge to acquire full ownership if they wish so. Another business model which is innovative and specific for EV is battery leasing, for which consumers purchase the car body and lease the battery only. Both types of leasing alleviate financial burden brought about by the high purchase price of EV. They also reduce uncertainties and shift some risks away from customers by providing some guarantee for battery and the residue value of the car.

It remains unclear whether these new business models are sufficient to compensate the shortcomings of technologies and make a substantial difference in facilitating EV adoption. If it is found to be a useful way for promoting EVs, car manufacturers should allocate some attention to business model innovation besides focusing on technical developments only; furthermore, since it would also help to achieve sustainability targets, the government could intervene to stimulate business model innovation besides implementing other incentives and policies (Birkin et al., 2007). Therefore, knowledge about the extent to which consumers change their preferences and behavior under different business models can provide insights into its potential in boosting EV sales, which is crucial for both government policy and car manufacturer decision-making.

An issue in assessing the impact of business models is that they may have different effects for different groups of consumers, which may cancel each other out at the aggregate level: for example, when new business models become available for all car types, some car drivers may switch from conventional vehicle (CV) to EV due to the lowered financial burden; while those who initially prefer EV may change to CV because the introduction of private leasing offers attractive monthly payments. If these two flows are around the same size in the population, the aggregate impact of business models becomes insignificant. Hence, we may risk ignoring these heterogeneous changes if we only examine aggregate changes. Therefore, uncovering these heterogeneous changes for different groups and identifying the groups that are most susceptible to business models is important, because this allows developing tailored policy or strategy making for different target groups.

Latent transition analysis (Collins and Lanza, 2010) offers an elegant solution to study these heterogeneous changes. As a typical latent class model, it assumes that the population consists of several unknown groups that have internally homogeneous preferences, which differ from those of other groups. In a new context, for example after a particular policy is implemented, preferences and choices of individuals may change and this behavioral change is represented by transitions of individuals between different groups. Therefore, instead of exploring direct changes between taste parameters in different contexts, latent transition models capture preference change by identifying changes in class membership. This model is powerful in describing behavioral change since it 1) easily incorporates opposite behavioral change by representing different directions in transition flows between groups, and 2) captures the relation between behavioral change patterns and initial preferences by the probability of transition between different classes. Despite the above mentioned advantages, latent transition analysis has only found limited application in transportation studies. Kroesen (2014, 2015) applied the method for investigating travel behavior evolution over time analyzing panel data. To the best of our knowledge, no prior research applied latent transition analysis to study the impact of policies or strategies in combination with stated preference data collections.

Considering the aforementioned research gaps, the aim of this paper is twofold. First, we contribute to the literature on EV adoption by examining the potential of business models (in particular leasing options) in facilitating EV adoption and substitution for internal combustion engine (ICE) vehicles. In particular, we first examine the aggregate impact of business models on EV preferences; second, we identify homogenous groups based on EV preferences and then reveal how different groups are differently affected by business models; third, we identify how individual specific variables (including socio-economic variables and attitudes) influence class membership and transition probabilities. The second aim of this paper is to contribute to the choice modeling literature by showing how latent transition analysis is able to uncover the different impacts of a business strategy or policy on the preference and behavior of different groups. This allows identifying the groups which are most susceptible to a particular strategy/policy. To the best of our knowledge, this study is the first to study induced behavioral change by using latent transition analysis to analyze data obtained from a stated choice experiment.

This remainder of this paper is organized as follows: section 2 presents the conceptual framework and specification of the models; section 3 introduces the data collection and survey design; section 4 discusses the estimation results of the models, and in the last section conclusions are drawn and implications discussed.

4.2. Modeling framework

There have been numerous studies, which aim to investigate the behavioral change induced by policies or strategies. Many of those collected data using stated choice experiments and adopt the framework of discrete choice models to ex-ante evaluate policies that either alter the characteristics of a certain alternative or change the preferences of individuals. In the former case, the policy can be represented as a change in one or more attributes in a stated choice experiment and the size of the policy impact can be deduced from the corresponding parameter (Hackbarth and Madlener, 2013; Hoen and Koetse, 2014). If the policy influences decision-making by affecting the preferences of individuals such as information or awareness campaigns, an option is to conceptualize it as a context variable, while the original choice tasks are coupled with different values of the context variable (Kim et al., 2014). The context variable enters the utility functions by interacting with attributes and the parameters of these interaction terms represent the preference change induced by policy. Another slightly different approach is to set up a stated choice experiment with multiple waves: for each choice task, respondents first give an answer under the status quo or a base context and then decide whether they will adapt their choice under a different context or after real experience with the policy of interest (Jensen et al., 2013). A separate set of taste parameters is estimated for each context (e.g. before and after the implementation of a policy) and the policy impact is captured by the differences between taste parameters of each model. Moreover, some policies or contexts may invoke completely different adaptation strategies beyond simply choosing a different alternative. Studies investigating such policies usually conduct stated adaptation experiments which use the status quo as the reference context and only ask for the behavior adaptation strategies under a new context (Arentze et al., 2004).

Previous studies which focus on preference change have two common limitations: first, they tend to only measure the average effect of policy for the entire population, while the effects for different people may vary in size or even direction. Furthermore, the above methods do not allow revealing the relation between people's behavioral change pattern and their initial preference profile. Those who have strong preferences for certain alternatives or who value certain attributes more than average may be less susceptible to change or tend to change their behavior in the direction opposite to others. If we can obtain such insights, we may come up with new and better ways to identify target groups for policies and strategies.

The provision of alternative business models can be considered as a new context for the traditional car purchase choice and is expected to change people's preferences and choice behavior. In order to collect data which allow the investigation of behavioral change under business models, we use a stated choice experiment with multiple waves (the details are discussed in section 3.2). For each choice task in the experiment, respondents first express their choice for the situation in which only buying a complete car is possible and no other business models are available. In this situation, respondents can choose between an internal combustion car, a battery electric car and a plug-in hybrid alternative. In the following waves, other situations are presented, in which alternative business models become available and respondents can adapt their choice and switch to another alternative.

In order to address the shortcomings in the previous literature regarding behavioral change, we adopt two approaches with a different focus to study consumers' behavioral change induced by business models. In the first approach, we investigate how average preferences of the entire population change due to the impact of business model. This a rather straightforward approach, but as discussed above, it has the disadvantage that changes may cancel out at the aggregate level. In the second approach, we overcome this shortcoming by studying how different latent classes have different switching behaviors. In the remainder of this section, we elaborate upon the conceptualization of these two approaches and also the specifications of the discrete choice and latent transition model.

4.2.1 Average impact of the business model

The first approach aims at exploring whether providing the option of leasing increases the popularity of EV among all car drivers; in other words, whether EV is chosen more often and becomes more preferred when leasing becomes available. We look at car drivers' choices between three different fuel types for the same car. Their choice depends on the utility of each alternative: the respondent is assumed to maximize utility and pick the one with the highest utility. This latent utility is determined by vehicle attribute values and consumer taste parameters. When a new business model becomes available, consumer preferences may change in contrast to when there is no business model, which leads to updated utilities of alternatives and finally changes in final choices. The impact of business models is therefore captured by the change of consumer preferences between two choices. Figure 1 illustrates this conceptualization.

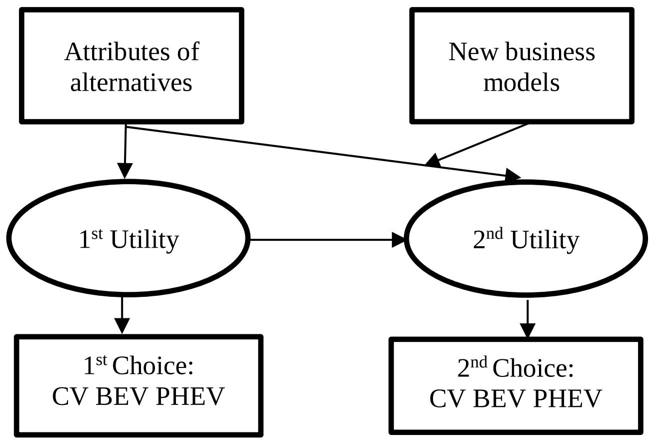

Figure 1. Conceptual model 1: average impact of business models

We estimate a discrete choice model to model the car type choice. In order to investigate the change of preference parameters under the influence of business model, we use two waves of choice data for model estimation: the first wave of choices made without business models and another wave of choices under a specific type of (or a combination of multiple) business model(s). The utility functions for the two waves of choices can be written as follows:

$$U_{nit}^{1} = \beta_{i0}^{1} + \boldsymbol{\beta_i^1}\, \boldsymbol{X_{it}} + \epsilon_{ni}^{1} + \varepsilon_{nit}^{1}$$

$$U_{nit}^{2} = \beta_{i0}^{2} + \boldsymbol{\beta_i^2} \boldsymbol{X_{it}} + \epsilon_{ni}^{2} + \varepsilon_{nit}^{2}$$

The two utility functions adopt exactly the same specification and the superscript denotes the corresponding choice. U_{nit} denotes the utility of alternative *i* in choice task *t* of person *n*. $\boldsymbol{X_{it}}$, $\boldsymbol{\beta_i}$ and β_{i0} represent the car attribute matrix, the attribute taste parameter matrix and the alternative specific constant respectively. ϵ_{ni} is the random panel effect which varies across individuals but remains constant over all choice tasks (under the same context) for the same respondent. It is assumed to be normally distributed with zero mean and standard deviation $\sigma_{\epsilon_i}^{1}$. ε_{nit} is an unobserved error term that is assumed to follow an extreme value distribution.

The estimated parameters in U_{nit}^{2} are specified as

$$\boldsymbol{\beta_i^2} = \boldsymbol{\eta}_i \boldsymbol{\beta_i^1}$$

$$\beta_{i0}^{2} = \eta_{i0} \beta_{i0}^{1}$$

$$\epsilon_{ni}^{2} = \eta_{i\epsilon}\, \epsilon_{ni}^{1}$$

in which $\boldsymbol{\eta}_i$, η_{i0} and $\eta_{i\epsilon}$ are all shift parameters. Since business models reduce some uncertainties surrounding EV which provides added-value, both the alternative specific constants and the scale of the random panel effect are expected to vary between the two waves of choices. Preferences for cost-related attributes are also expected to change. First, consumers may become less sensitive towards purchase price since the financial burden imposed by this price is relieved by business models. Second, when consumers are only aware of the huge differences of purchase price between EV and CV, the savings on operational cost (such as energy cost) may seem small. Under the context of leasing, the one-off purchase price is transferred into an explicit monthly payment which is similar to operational cost. Therefore, operational cost attributes become more salient and the tradeoff between operational cost and a monthly payment is also easier, which may lead to a change in preference for operational cost attributes. In addition, taste parameters for other attributes may also change due to the following two mechanisms: first, some EV related attributes may be ignored initially since consumers may exclude EV from consideration due to issues such as high cost or uncertainty; after business models are provided, these consumers may start to seriously consider EV and those previously ignored attributes become significant; second, when the purchase price of EV has to be paid at once which poses a large economic burden, consumers may have very high requirement for EV performance and ease of use in order to justify this burden; while this requirement may become less stringent if they can adopt via leasing.. If a shift parameter significantly differs from 1, business models are considered to have an impact on the corresponding parameter. The size of this impact can be reflected by the difference of willingness-to-pay values between the two waves.

The joint likelihood function for person *n* is thus:

$$\mathrm{L} = \int_{\epsilon} \prod_{t\in T} \prod_{i\in J} P_{nit}^{1}(y_{nit}^{1} = 1|\boldsymbol{X_{it}};\ \boldsymbol{\beta^{1}}, \beta_{i0}^{1}, \sigma_{\epsilon_i}^{1})^{y_{nit}^{1}}\ P_{nit}^{2}(y_{nit}^{2} = 1|\boldsymbol{X_{it}};\ \boldsymbol{\beta^{2}},\ \beta_{i0}^{2}, \sigma_{\epsilon_i}^{2})^{y_{nit}^{2}} \frac{1}{\sigma_{\epsilon_i}^{1}} \Phi(\frac{\epsilon_{ni}^{1}}{\sigma_{\epsilon_i}^{1}}) \mathrm{d}\epsilon_{nJ}$$

where the first and second term denote the probability of choosing alternative *i* in choice task *t* in terms of the first and second choice. Pythonbiogeme (Bierlaire, 2016) is applied for the estimation of this model.

4.2.2 Heterogeneous impact of business models

In contrast to the first approach, the second approach focuses on the heterogeneity of consumer preferences and their behavioral change. The entire population is assumed to consist of several groups; preferences for fuel types and other car attributes are homogeneous within each group and heterogeneous across different groups. When alternative business models become available, some car drivers' preferences will change and become identical with another group; in other words, these persons convert their group membership and flow into another group because of the presence of new business models. Therefore, the impact of business models is captured by the flows between different groups. The probabilities of flowing into other groups can be called "transitional probabilities" and are assumed to be conditional on the original group membership. Furthermore, we wish to explore the impact of individual-specific variables on group membership and transition probabilities. These effects are distinct for each group as well. Figure 2 is an illustration of the second conceptual model.

A latent class choice model can be estimated to uncover the preference heterogeneity and classify people into different groups based on their preferences, and a latent transition model is estimated to reveal the behavioral change due to the impact of business models which appears as transition flows between different classes.

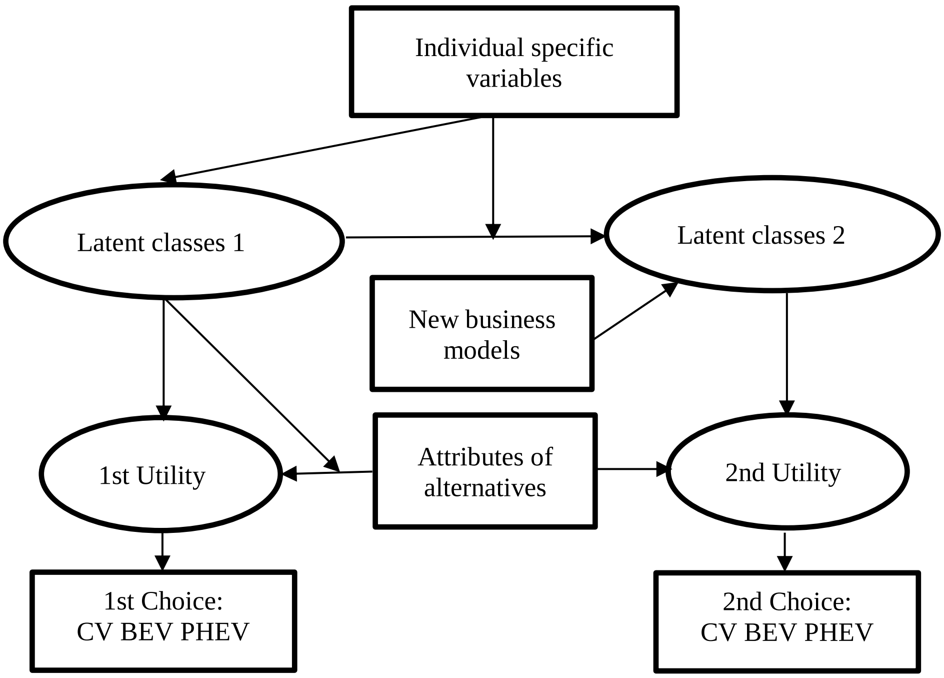

Figure 2. Conceptual model 2: heterogeneous impact of business models

We can estimate all model components simultaneously via one-step maximum likelihood; however, if we include the covariates simultaneously in the model, the parameters of the latent class choice model may shift depending on the relationship between the latent class indicators (choices) and the covariates (Di Mari et al., 2016; Nylund-Gibson et al., 2014). This does not fit with the conceptualization since the latent class variable is supposed to capture preference heterogeneity free from the influence of covariates. Therefore, in order to circumvent this problem, we applied the three-step procedure (Asparouhov and Muthén, 2014) in estimating the latent class models. The latent class choice model is estimated first (step 1). The utility of alternative *i* for members of class *k* when business models are not available is

$$U_{ik} = \beta_{ik0} + \boldsymbol{\beta_{ik}} \boldsymbol{X_i} + \varepsilon_{ni}$$

in which the set of attribute taste parameters $\boldsymbol{\beta_{ik}}$ and alternative specific constant β_{ik0} are class specific.

In step 2, we use the latent class posterior distributions to assign a most likely class for each respondent. Every person is assigned class membership *c1* based on their first wave of responses when there is no business model. Class membership *c2* is based on their second wave of adapted responses when leasing becomes available. Eventually, the class membership model and the latent transition model are estimated (step 3). In the initial class membership model, the personal characteristics z_n of individual *n* influence the probability of belonging to class *k* in his first wave of choice (when there is no new business model):

$$P(c1 = k) = \frac{exp(\gamma_k + \sum_{r=1}^{R} \gamma_{kr} z_{nr})}{\sum_{x=1}^{K} \exp(\gamma_x + \sum_{r=1}^{R} \gamma_{xr} z_{nr})}$$

in which z_n are covariates, and intercept γ_k and effects of covariates γ_{kr} are estimated for each class. One of the classes is set as reference for which all parameters are fixed to zero.

The latent transition model describes the transition probabilities between different latent classes and the effects of individual specific variables on these probabilities. The probability of a person transferring to class *j* when innovate business models are available if he first belongs to class *k* is written as

$$P(c2 = j|c1 = k) = \frac{exp(\gamma_j + \gamma_{jk} + \sum_{r=1}^{R} \gamma_{jkr} z_{nr})}{\sum_{s=1}^{K} \exp(\gamma_s + \gamma_{sk} + \sum_{r=1}^{R} \gamma_{skr} z_{nr})}$$

in which γ_j, γ_{jk} and γ_{jkr} are parameters which are estimated. Similar to the class membership model, all parameters are constrained to zero for a class (in c2) set as reference.

This 3-step procedure ensures that the estimation of the latent class choice model is independent from the class membership model. We applied LatentGold (Vermunt and Magidson, 2016) for the latent class choice model estimation and class assignment of each respondent. The class membership model and latent transition model are estimated by Mplus (Muthén and Muthén, 2010).

4.3. Data collection

4.3.1 Survey design and sample statistics

The data used in this study were collected in June 2016 through an online survey based on a platform of the Urban Planning Group in Eindhoven University of Technology. The respondents were recruited randomly by a marketing research company from their panel in the Netherlands. The target population is set to be potential car buyers. Therefore, we selected respondents who hold a driver license and are either car owners or expect to buy a car in the following three years. Since business models usually apply to new car buyers (in our case: private cars only), people who plan to buy a second-hand car or company leasing car are excluded. The final sample contains 1003 respondents.

Apart from the choice experiment which is introduced in the following section, the online survey also included questions regarding the respondents' socio-demographics, current mobility behavior and the specifications of the next car they expect to purchase. Table 1 presented the socio-demographics and basic characteristics of car ownership of the sample.

Furthermore, we measured respondents' knowledge on EV and their attitudes towards leasing. Ten statements related to leasing are included in the survey to examine people's attitudes. Each statement describes a possible motivation or reason for preferring/disliking leasing, and is rated by a 5-point Likert scale ranging from ‘‘completely disagree” to ‘‘completely agree”. We performed principal axis factoring analysis with varimax rotation to explore whether there are any common factors underlying the responses. In total three factors are identified. Table 2 lists the information of all the statements and the extracted factors. Only factor loadings > 0.3 are presented. The factor of pro-convenience represents the extent to which someone finds leasing to be beneficial because it saves trouble and reduces risk. A high score on the pro-ownership factor implies that the respondent finds car ownership to be irreplaceable and carsharing is less preferred. The last factor of pro EV-leasing reflects the attitude towards the applicability of leasing for EV. From the original responses to statements we can see that in general many people recognize and appreciate the convenience brought by private leasing, but the vast majority are more or less emotionally attached to owning a vehicle and do not like the idea of leasing. As for the applicability of leasing for EV, the close to neutral average score and the relatively small standard deviation show that many people may not have sufficient knowledge to hold an opinion.

Table 1. Sample Characteristics

Items		Value	Percentage
Socio-Demographics	Gender	Male	51.7
		Female	48.3
	Age	<=35 years	25.0
		36-50 years	24.0
		51-65 years	30.8
		>=66 years	19.2
	Number of household members	1 person	16.8
		2 person	44.3
		3 person	16.7
		>=4 person	22.2
	Education level	No high education	56.6
		With high education*	43.4
	Monthly net personal income (euro)	<625	6.8
		625-1250	10.6
		1251-1875	18.9
		1876-2500	30.3
		2501-3125	17.9
		>3125	15.5
Information regarding car ownership and the expected car	Number of cars	0	1.0
		1	68.4
		2	27.6
		More than 2	3.0
	Purchase cost of expected car (1000 euro)	10-15:	38.7
		16-20:	24.2
		20-30:	24.6
		>30:	12.5
	Fuel type of expected car	Gasoline	77.3
		Diesel	9.9
		LPG	1.6
		Hybrid	4.7
		BEV (Battery electric vehicle)	2.6
		PHEV (Plug-in Hybrid electric vehicle)	2.4
		Others	1.6

Note:*: Those who received higher vocational or university education.

We also included three questions to measure people's knowledge about EVs since it is expected to influence one's EV preferences. The respondents are asked how much they know about the differences between PHEV and BEV, car manufacturers that produce EVs and EV incentive policies. Principal axis factoring extracted a single factor from the answers which represents the level of knowledge regarding EV. The measurements and estimates of this factor can also be found in Table 2. All factor scores are standardized when they are incorporated in the following analyses.

4.3.2 Choice experiment design

The choice experiment assumes a context situation in which respondents are buying their next car. Respondents have to assume that three versions of the same car are available which only differ in propulsion technologies, namely conventional car (CV) powered by petrol or diesel, full battery electric vehicle (BEV) and plugin hybrid electric vehicle (PHEV). The conventional car alternative is the reference alternative and all attribute values are fixed throughout the entire experiment. The experiment is made respondent-specific to increase the realism of the choice experiment: the value of its purchase price and fuel cost are taken from the respondents' answers to previous questions in the questionnaire in which respondents describes their most likely car they will purchase next. However, for people who indicated earlier that they expected to buy an EV, the price of the conventional car alternative is set to approximate a gasoline car comparable to the EV.

Table 2. Attitudinal statements, scores and the measurement model of latent attitudinal variables

Statements	Average	Standard deviation	Factor loading
Factor 1 Pro-convenience			
Leasing is nice because I can switch cars regularly.	2.78	1.030	0.529
Leasing is nice because the risks of maintenance and damage are not for me.	3.33	0.928	0.833
Leasing is nice because I know exactly how much I have to pay every month.	3.34	0.913	0.866
I find it important that a lot of hassle is gone when leasing a car.	3.12	0.931	0.666
Factor 2 Pro-ownership			
I prefer to pay the total price at one time than paying each month.	3.73	0.977	0.735
I prefer to own a car than to lease one.	3.89	0.917	0.858
Car lease is more suitable for company cars than for private cars.	3.55	0.967	0.599
I do not want to lease a car because it is more expensive than buying a car.	3.49	0.950	0.545
Factor 3 Pro EV leasing			
Leasing contract is more suitable for EV than for conventional cars.	2.90	0.849	0.736
EV batteries are better to be leased than purchased.	3.14	0.758	0.576
Knowledge for EV			
Knowledge regarding the difference between BEV and PHEV	2.49 (max 4)	1.040	0.551
Knowledge regarding EV brands	2.19 (max 3)	1.107	0.719
Knowledge regarding EV policy incentives	1.69 (max 3)	0.626	0.616

In order to disentangle the effect of alternative business models and more clearly observe the change in choices when they become available, we used a sequential stated choice experiment. In each choice task, the respondents have to answer three questions: they were first asked to choose an alternative when no extra business models are provided and they have to pay the full purchase price (wave 1). Next, assuming that battery leasing becomes available for BEV, we provide extra information of car body price and monthly battery leasing cost for BEV, and respondents make an updated choice (wave 2). Finally, they make another decision assuming that leasing also becomes available for all three car types, the monthly leasing price for all three alternatives are shown (wave 3). All monthly payments for leasing are calculated based on the purchase price and differ according to the expected annual mileage reported by respondents, which imitates the common pricing scheme of current private leasing. A similar sequential setup can be found in Kim et al. (2017)

Each alternative is described by purchase price, energy cost and driving range. BEV has several additional attributes including fast charging station density, fast charging duration and policy incentives. We also included an innovative business model “mobility guarantee” as an attribute to test its impact on BEV preference. Mobility guarantee is a value-adding service offered by some BEV manufacturers, which provides a substitute conventional car for a short period every year to cover the occasional long trips of EV owners. PHEV has an additional attribute: the all-electric range, which is the range it covers when it is solely powered by battery. Table 3 lists the selected attributes and their levels.

Table 3. Selected attributes and their levels

Attribute	Alternative	Level 1	Level 2	Level 3
Purchase price	Conventional car (PP)	Defined by respondent		
	BEV(euro)	0.8*PP +5000	PP + 5000	1.2*PP+5000
	PHEV(euro)	0.8*PP +5000	PP + 5000	1.2*PP+5000
Energy cost	Conventional car	Defined by respondent		
	BEV(euro/100km)	2	4	6
	PHEV(euro/100km)	2	4	6
All-electric range (AER)	PHEV(km)	30	70	110
Driving range	Conventional car (km)	600		
	BEV(km)	150	300	450
	PHEV(km)	600 + AER		
Fast charging station density	BEV(km) (highway/urban)	50/0	75/5	100/10
Fast charging duration	BEV(minutes)	10	20	30
Policy incentive	BEV	None	Road tax exemption	Free public parking
Mobility guarantee	BEV(days per year)	0	7	14

Some of the attributes of BEV may be unfamiliar for car drivers if they have never considered nor have much knowledge of EV. Therefore, in every page with a choice task, we added a link to more detailed description and explanation of these attributes. Charging infrastructure density is found to be significant in many previous studies (Hackbarth and Madlener, 2013; Jensen et al., 2013; Rasouli and Timmermans, 2013; Tanaka et al., 2014). These studies have generally operationalized this variable by the percentage of fuel stations equipped with charging infrastructure or detour time relative to the nearest fuel station. These formulations are hard to be directly applied by policy makers in planning, and they did not note the difference of distribution of charging stations in urban areas and on highways. Therefore, we adopt a rather different operationalization: first, we specify only fast charging stations, since slow charging poles is not a feasible solution when range is almost depleted during a long trip; second, we use different descriptions for highway and urban area. On the highway, we give the average distance between two stations, and for the urban area we give the average distance between the closest station and the places which respondents visit most often.

The choice tasks were generated using a D-efficient optimal design by Ngene (ChoiceMetrics, 2010). In total, 12 choice tasks were constructed and split into two blocks of 6 choice tasks. Each respondent was randomly assigned to one of the two blocks. Figure 3 shows an example of a choice task.

[Choice task 3 / 6 Question 1 / 3]

Assume you can choose from the following three cars:

Attributes	Conventional vehicle	Battery electric vehicle (BEV)	Plug-in hybrid vehicle (PHEV)
Fuel cost	€13 per 100 km	**€2** per 100 km	**€4** per 100 km
Driving range with full fuel tank/battery	600km	**450km**	Electric range: **30km** Total range: **630km**
Fast charging station density		**On highway: one station every 100 km** **In cities:** Within **10 minutes** ride from the often visited locations	
Fast charging duration(till 80% of battery capacity)		**20 minutes**	
Governmental **incentive policies**	None	**Free public parking**	None
Number of days per year that you can make additional use of conventional car	n.a.	**14 days** per year	n.a.

We now ask you **three questions** regarding the choice between **these three cars**.

1. Suppose you only have the option to **purchase** the cars described above. The prices Of these three cars are listed below. Which of these three cars would you buy?

Conventional vehicle	Electric vehicle (BEV)	Plug-in hybrid vehicle (PHEV)
€24000	**€33800**	**€29000**
○	○	○

(a)1st question

Your previous choice: [X]	[X]*Conventional vehicle* €24000	Battery electric vehicle €33800	Plug-in Hybrid vehicle €29000

2. Now for **battery electric vehicle, you can choose to buy the car body only and lease the battery pack for a fixed payment per month. The price of the car body and the monthly leasing payment of the battery pack are listed below. Which car will you choose?**

Purchase	Battery lease
I keep my previous choice	**Battery electric vehicle** **€28800** **+€80 per month** **for maximum milage of 15.000km per year, 5 cent per extra km**
○	○

(b) 2nd question

Your previous choice: [X]	Conventional vehicle €24000	[X] *Battery electric vehicle* €28800 +€80 per month for maximum mileage of 15.000km per year, 5 cent per extra km	Plug-in Hybrid vehicle (PHEV) €29000

3. Suppose you can also **lease** one of the three cars. The **monthly lease fee** for these three cars are listed below. **Would you like to lease one of these three cars** Or will you keep your previous choice?

	Private lease for maximum mileage of **15.000km** per year, **10 cent** per extra km		
I keep my previous choice	**Conventional vehicle** **€377 per month**	**Battery electric vehicle** **€533 per month**	**Plug-in Hybrid vehicle (PHEV)** **€473 per month**
○	○	○	○

(c) 3rd question

Figure 3. Example of choice task (translated from Dutch)

4.4. Results

4.4.1 The average impact of business model

In each model, we can assess the change between two waves of choices; therefore, we estimated two models: the first model examines the first (no business model) and second (battery leasing) waves of choice; the second model looks at the first and third (battery leasing + car leasing) waves. The models are estimated using 1000 Halton draws. For both models, we first used the general form of the utility equation and estimated all shift parameters $\boldsymbol{\eta}_i$, η_{i0} and $\eta_{i\epsilon}$. However, none of the attribute shift parameters $\boldsymbol{\eta}_i$ are significantly different from 1. Therefore, in order to arrive at a parsimonious model, we assumed that attribute taste parameters do not vary across different contexts by fixing $\boldsymbol{\eta}_i$to 1 and re-estimated the model.

Table 4. Estimation result of business model impact model

			Only battery leasing available			**All leasing available**		
Name			Value	Std. err	t-value	Value	Std err	t-value
Constants and panel effects								
Alternative specific constants	BEV	1st	4.16	0.492	8.44	4.28	0.460	9.29
		Shift parameter	1.133	0.0311	4.27	0.977*	0.0232	-1.00
	PHEV	1st	3.17	0.389	8.15	3.61	0.370	9.75
		Shift parameter				0.885	0.0281	-4.08
Standard deviation of panel effects	BEV	1st	4.30	0.218	19.73	4.06	0.178	22.78
		Shift parameter	1.105	0.0371	2.82	1.014*	0.0269	0.54
	PHEV	1st	4.59	0.297	15.42	4.29	0.202	21.21
		Shift parameter				1.045*	0.0241	1.85
Attributes								
Relative purchase price (100%)[1]			-6.33	0.339	-18.66	-6.70	0.327	-20.47
Energy cost (euro/100km)			-0.215	0.0239	-9.01	-0.212	0.0226	-9.39
Driving range (100km)			0.131	0.0482	2.72	0.117	0.0478	2.45
All-electric range (100km)			0.500	0.159	3.14	0.619	0.147	4.20
Fast charging availability (per 100km)			-1.320	0.295	-4.48	-0.791	0.289	-2.74
Fast charging duration (hour)			-0.191*	0.347	-0.55	0.00911*	0.347	0.03
Road tax exemption			0.348	0.0764	4.55	0.211	0.0705	3.00
Free public parking			-0.231	0.0818	-2.82	-0.0965*	0.0790	-1.22
Mobility guarantee (week)			0.0526*	0.0702	0.75	0.0782*	0.0658	1.19

*: Estimate is insignificant at p>0.05

1: The relative purchase price is the ratio between the purchase price of the respective vehicle and price of the reference CV.

The left side of Table 4 shows the estimation result of the model when only battery leasing of BEV is available in the second choice. The shift parameter of the ASC of BEV is significantly larger than one, which reveals the power of providing battery leasing in increasing the preference for BEV. In terms of willingness-to-pay, for a person whose stated purchase price is 15,000 euro, the WTP for BEV is 1311 euro higher than when battery leasing is not available This implies that when vehicle leasing is not available, introducing battery leasing is an effective way to increase BEV sales.

The right side of the same table displays the result when both battery leasing and car leasing are available. The shift parameter of the ASC of BEV becomes insignificantly different from one, while the corresponding parameter for PHEV is significantly less than one. This implies that when leasing is provided to all three types of vehicles, the attractiveness of BEV at the aggregated level is rather unaffected while the utility of PHEV slightly decreases (a 929 euro decrease in terms of WTP) and its probability of being chosen is reduced when all else is held equal.

The effects of the rest of the attributes in both models all have expected signs that are based on findings in previous studies. Relative purchase price and energy cost negatively affect utility which is intuitive. The driving range of BEV and the all-electric range of PHEV are both found to have a significant and positive impact on the utility of BEV and PHEV. The negative sign of fast charging availability in this model indicates that consumers dislike long distances between charging stations and prefer a denser fast charging network. The duration of fast charging does not significantly affect the utility of BEV. This result contradicts the findings of many previous studies (Bockarjova et al., 2014; Chorus et al., 2013; Hackbarth and Madlener, 2013). It may be due to two reasons. First, in this study we only investigate the preference for fast charging and use a rather narrow range for this attribute value (10-30min) while many studies use a wide range including both fast and slow charging (for example 10min – 8 hours). This result may reflect people's genuine preference that as long as the fast charging time falls in the range given in the choice experiment, it does not make a difference for people. A second reason may be that only a small group of people have a significant preference for shorter charging time and the average coefficient for the entire population does not reach significance. As for government incentive policies for EV, road tax exemption is effective, whereas free public parking does not have any significant influence on the choice of EV adoption. Furthermore, although the parameter for mobility guarantee is positive which suggests that consumers indeed prefer having such service, its size is quite small and is not statistically significant.

The estimated models demonstrate that when battery leasing is introduced alone, it has a significant positive impact on BEV's popularity. On the other hand, when vehicle leasing also becomes available for all three car types, the results imply that at an aggregate level, the business models we tested may not be sufficient to overcome the deficiencies of EV as a product and shift conventional car buyers towards EV adoption. However, we cannot definitely conclude that business models are not effective since only two business models are tested and both are set under a fixed pricing scheme. Whether the business model is provided to all types of cars and its detailed pricing scheme are both crucial to its final success. In the next section, we will explore how the impact of business model varies for people with different preferences.

4.4.2 The Heterogeneous impact of business model on different groups

The analysis in the above section shows that the aggregate effect of business models is rather limited in our sample; in other words, it does not significantly increase the popularity of EV. In order to reveal the heterogeneity regarding preferences for car types between groups and show the varied influence of business models on each group, we now estimate a latent class choice model and conduct a latent transition analysis. Since battery leasing alone only affects BEV and its impact is rather clear, it either has a positive impact on BEV utility or the effect is insignificant because people can only switch from CV to BEV but not the other way around. In other words, it does not have opposite effects on people. When vehicle leasing is also introduced and made available for all alternatives, people may switch in both ways (from CV to BEV and vice versa). Therefore, in this section we only use choices to the first and third questions (wave 1 and 3) to study the more complex behavioral change when both battery leasing and car leasing become available.

4.4.2.1 Latent class model: car type preference

In order to identify the optimal number of latent classes, we estimated models ranging from one to ten classes for both choices separately. Table 5 presents the relevant model fit statistics. In the model of choices in wave 1, the 5-class model has the lowest BIC value. As for the choices in wave 3, although the BIC value is the lowest for 6-class model, its reduction from that of 5-class is rather small and the additional class is not essentially different from the already existing five classes. Therefore, considering both model fit and complexity, we select the 5-class model as optimal.

Table 5. Model fit of the latent class choice models

	Number of classes	LL	BIC	Npar	$R^2(0)$	R^2
Choice in wave 1	1	-5172	10419	11	0.2314	0.0427
	2	-4067	8294	23	0.5428	0.4306
	3	-3828	7899	35	0.6315	0.5410
	4	-3712	7749	47	0.6628	0.5800
	5	-3610	7628	59	0.6873	0.6106
	6	-3571	7632	71	0.7147	0.6447
	7	-3533	7640	83	0.7326	0.6669
	8	-3507	7670	95	0.7488	0.6871
	9	-3495	7729	107	0.7583	0.6989
	10	-3475	7771	119	0.7696	0.7131
Choice in wave 3	1	-5061	10198	11	0.2491	0.0387
	2	-3975	8108	23	0.5547	0.4299
	3	-3732	7706	35	0.6405	0.5398
	4	-3623	7570	47	0.6683	0.5754
	5	-3532	7472	59	0.6921	0.6058
	6	-3477	7445	71	0.7141	0.6340
	7	-3437	7448	83	0.7407	0.6680
	8	-3411	7478	95	0.7535	0.6845
	9	-3396	7531	107	0.7685	0.7037
	10	-3380	7582	119	0.7721	0.7083

Table 6 presents the results of the latent class choice model including the choice profile and preference parameters of each class.

The majority of the population are strict (prospective) CV buyers (~49%). They choose CV in 97% of choice situations. Most of the EV specific attributes are insignificant, which is plausible since they have a strong preference for CV regardless of the specification of EV.

The second class (~13% of sample population) still chooses CV more than half of the time (54%), but they also choose BEV in 40% of the choice situations on average; therefore, it is labelled as the CV+BEV class. All taste parameters for car attributes and charging infrastructure are significant (except energy cost) and have the expected sign, while neither of incentive policies nor mobility guarantee have any significant influence. This implies that this class seriously trades off between the three car types based on their attributes.

The third class (17-20% of sample population) has a stronger interest in EV compared to class 2, demonstrated by the fact that they only choose CV less than half of the time (45%). They also prefer PHEV to BEV in contrast to the CV + BEV class. All attributes regarding CV and BEV are significant and with the expected sign. Mobility guarantee also has a significant and positive impact for this class, showing that this value-adding service does have an influence on people who are highly interested in EVs.

The fourth class (14% of sample population) is labelled as EV buyers since they almost never choose CV (only 3.3%). The parameter for fast charging availability is not significant and the parameter for charging duration is positive; this is rather unexpected and may be due to the fact that they have such strong interest in EV that they do not mind the inconveniences brought by charging. Government incentives and mobility guarantees do not have significant extra stimulation either given their already high interest.

The fifth class take a rather small share of the population (~5%) and are rather strict PHEV buyers since they choose PHEV in almost 90% of choice situations. Most parameter estimates are as expected, except that the price parameter is insignificant.

Table 6. Estimates of latent class choice model

	Class1 (CV buyers)	Class 2 (CV + BEV)	Class 3 (Serious interest in EV)	Class 4 (EV buyers)	Class 5 (PHEV buyers)
Class size (%), N=1003					
1st choice	49.2	12.3	19.8	14.1	4.8
2nd choice	49.9	13.6	16.6	14.8	5.1
Choice share within each class (%)					
CV	97.1	53.6	44.7	3.3	5.4
BEV	1.4	40.1	15.6	67.9	6.9
PHEV	1.5	6.3	39.7	28.8	87.7
Taste parameter estimates					
CV ASC	**-4.846**	**-1.022**	**-8.346**	**-5.457**	2.346
BEV ASC	**4.922**	**2.027**	**3.138**	**2.857**	**-7.220**
PHEV ASC	-0.075	**-1.005**	**5.208**	**2.599**	**4.873**
Relative purchase price	**-10.080**	**-2.915**	**-12.728**	**-5.096**	1.261
Energy cost	*0.139*	-0.016	**-0.369**	**-0.399**	**-0.420**
Driving range	0.030	**0.122**	**0.597**	**0.284**	*0.463*
All-electric range	-0.529	**0.855**	-0.060	**0.528**	*1.209*
Fast charging availability	**-7.967**	**-0.617**	*-1.273*	-0.684	**5.081**
Fast charging duration	**-3.587**	**-0.884**	**-4.099**	**6.392**	**5.327**
Road tax exemption	3.628	0.050	**0.510**	-0.019	**1.301**
Free public parking	-6.078	-0.042	-0.132	-0.145	**-2.912**
Mobility guarantee	*-0.553*	-0.014	**0.364**	**-0.701**	**1.541**
R^2	0.917	0.226	0.413	0.487	0.686

Notes: 1. Estimates in bold are significant at p<0.05. Estimates in italic are significant at p<0.10.
2. We applied effects coding for the ASCs of the three alternatives: only two were estimated.

Table 7 presents the class membership model in the case of the 1st choice. In general, few individual variables have a significant influence on the class membership, but the effects of covariates which are significant are all reasonable. The probability of belonging to strict CV buyer class is higher for men, people with lower education, fewer household members, less knowledge of EV and lower frequency of commuting by car. Younger people and more frequent public transport users are more likely to be a member of CV + BEV class. Females, retired people, frequent car commuters and people who expect to buy cheaper cars are less likely to belong to the group which has serious interest in EV. The probability of being a member of EV buyers decreases with age, public transport and car commuting frequency.

Table 7. Class membership model of first choice

	1 CV buyers	2 CV + BEV	3 Serious interest in EV	4 EV buyers
Sex (=female)	*-0.640*	-0.459	*-0.590*	-0.481
Age	-0.009	**-0.036**	-0.011	*-0.031*
Number of household	**-0.358**	-0.208	-0.151	-0.185
Have 4-12-year-old kid	0.703	0.162	0.181	0.492
Employed	0.251	-0.088	-0.541	0.609
Retired	-0.593	-0.545	**-1.288**	-0.632
Income	0.051	0.086	-0.145	-0.180
Education	*-0.440*	-0.248	0.068	-0.085
Knowledge of EV	**-0.558**	-0.044	0.229	-0.042
Experience with EV	-0.624	-0.407	-0.584	0.302
Car price	-0.010	-0.021	**-0.017**	-0.008
Annual mileage	0.073	0.037	0.196	0.162
Frequency of long trip	0.056	-0.015	0.113	0.010
Have own parking spot	0.004	-0.126	0.118	0.544
Buying a second car	0.315	0.431	0.047	0.102
Public transport frequency	-0.126	*-0.236*	-0.156	*-0.23*
Car commuting frequency	**-0.265**	-0.207	**-0.253**	**-0.380**
Intercept	**6.647**	**7.301**	**4.434**	**5.439**

Notes: Estimates in bold are significant at p<0.05. Estimates in italic are significant at p<0.10. Reference class is PHEV buyers.

4.4.2.2 Latent transition model: the impact of business models

Before conducting the latent transition analysis, we need to examine whether the assumption of measurement invariance holds. This property basically means that identical response patterns will be assigned to the same classes in both models for the two choices. This makes the interpretation of transition between clusters intuitive (the individual who gives the same answers in two waves will stay in the same class). We first estimate the latent class choice model separately for two choices (unconstrained model) and then estimate one single model after stacking the data from two waves together (constrained model). We use the BIC value to determine the best model (Kroesen, 2015). The result shows that the constrained model fits better (BIC=14773) than the unconstrained model (BIC=15179) which indicates that measurement invariance across the two waves upholds.

In the standard 3-step procedure, the extent of misclassification is accounted for in the final step of estimating the latent transition model. However, in order to keep a simple model, considering that the entropy (0.865)[15] of the latent class choice model is rather high which suggests that the classification error is small, we did not make any adjustments and directly used the most likely class for each respondent which is derived from the second step.

Considering that very few people transferred into or away from the PHEV buyer class in the second wave and the class itself is quite small in size, we excluded all respondents of the PHEV buyer class (in both waves) from the transition analysis. This left us with 949 respondents and the transition between the rest of four classes are analyzed in the final model. Table 8 presents the estimation results of the class membership model of the second wave of choices. These parameter estimates are used to generate the matrix of transition probabilities of the entire sample shown in Table 9. In order to make the preference differences between classes more tangible, we also provided the WTP estimates for each class (involved in transition analysis) and their relative differences in Table 10. We can clearly see that the WTP for both ASC and attributes differ vastly between groups which reflect the difference between taste parameters we discussed earlier. The class membership of the second wave of choices is assumed to be determined by both the membership in the first wave of choices and several individual specific variables. The effects of these individual variables are also conditional on the membership in the first wave and are therefore class-specific. Since the latent transition model is quite data-intensive and the flows between classes are rather small (statistics-wise), we only include five covariates: the expected price of next car, knowledge of EV and three factors regarding attitudes towards leasing. The five covariates are expected to have a direct influence on the transition probability of individuals. We used covariates which are not included in the initial class membership model, since the initial class membership concerns preferences for car types, while in the transition model we wish to explore the impact of leasing attitudes on transition probabilities and these attitudes are not expected to be related with car type preferences. Business models may be less attractive for people who plan to buy a more expensive car since they are expected to have less financial pressure. People who are familiar with EV or have a relatively positive attitude for leasing are more likely to switch to adopting EV when leasing becomes available and lessens their financial burden.

In the first row of Table 8 we can find the intercepts γ_j for all classes in wave 2 of choices: they are all significantly negative, which implies that, all else being equal, a member of the reference CV+BEV class has a larger probability of staying in the same class after leasing becomes available. The slopes of wave 1 classes on wave 2 classes correspond to γ_{jk}: we can see that the slopes of each class (in wave 1) on the same corresponding classes in wave 2 are

[15] The entropy of a model is a measure of classification uncertainty. It takes a value between 0 and 1, higher value implies a higher certainty in classification.

the largest compared to the slopes on other classes, which implies that the majority of people remain inert under the presence of business models.

Table 9 presents the matrix of transition probabilities. The diagonal probabilities are indeed the largest compared to the off-diagonal probabilities in the same row. Strict CV buyers and EV buyers are groups with the highest probability of remaining unchanged (0.94 and 0.89), which suggests that both groups have strong intrinsic preferences for their favorite car type and are hardly affected by other factors (in this case being a business model). As for the CV+ BEV class and the serious interest in EV class, their probability of remaining unchanged is almost the same (75%) and both significantly lower than the other two groups. This result is plausible since the choices of strict CV buyers and EV buyers already demonstrated non-trading behavior (constantly choosing or ignoring the same alternative) in the choice experiment and are less likely to be affected by changes in other attributes and contexts.

The off-diagonal probabilities represent the flows between classes due to the effect of business models. Based on the size of each class, we can calculate that in total 12.7% of the sample population switched classes. Since in the table we rank the classes based on their choice share of CV (from highest to lowest), the cells above the diagonal line represent flows towards classes with higher EV choice share, while the cells below represent the change of increasing choice share of CV. We found that 6.3% choose more EVs while 6.4% choose more CVs after the presence of business models, which indeed do cancel each other out on the aggregate level as earlier suggested. Hence, this resonates with the result from the discrete choice model, which shows the relative insignificant aggregate impact of business models.

Now we take a closer look at the value of each probability estimate. These transition probabilities have strong practical relevance, since we can identify the transition patterns of each group and diversify our strategies and policies in facilitating the behavioral change we wish to encourage.

Table 8. Parameter estimates of latent class membership of second choice

		Wave 2 class membership			
Wave 1 class membership	**Parameters**	**CV**	**Serious Interest EV**	**EV Buyer**	**CV+BEV**
	Intercept	-1.190	**-2.960**	**-2.843**	0
CV	Slope	**4.284**	**3.391**	/	0
	Price	-0.003	**-0.069**		0
	Knowledge EV	**-0.580**	-0.301		0
	Pro-convenience	-0.366	-0.155		0
	Pro-ownership	**0.511**	*-0.651*		0
	Pro-EV leasing	-0.293	**1.142**		0
Serious Interest EV	Slope	1.451	**6.821**	**3.287**	0
	Price	-0.054	-0.042	-0.043	0
	Knowledge EV	0.289	0.178	0.376	0
	Pro-convenience	-0.044	-0.265	-0.284	0
	Pro-ownership	-0.591	-0.762	-0.680	0
	Pro-EV leasing	0.313	-0.129	0.171	0
EV	Slope	/	**4.273**	**6.204**	0
	Price		-0.022	-0.013	0
	Knowledge EV		-0.009	**0.832**	0
	Pro-convenience		0.322	-0.279	0
	Pro-ownership		-0.868	-0.371	0
	Pro-EV leasing		0.224	-0.502	0
CV+BEV	Slope	0	0	0	0
	Price	-0.066	-0.004	0.011	0
	Knowledge EV	0.493	*0.894*	0.258	0
	Pro-convenience	0.178	0.595	-0.496	0
	Pro-ownership	**-0.584**	0.421	0.332	0
	Pro-EV leasing	-0.238	0.045	**0.519**	0

Notes: Estimates in bold are significant at $p<0.05$. Estimates in italic are significant at $p<0.10$.

Table 9. Matrix of transition probabilities

N=949	Wave 2			
Wave 1	CV	CV+BEV	Serious Interest EV	EV
CV	0.94	0.05	0.01	0
CV+ BEV	0.09	0.75	0.07	0.09
Serious Interest EV	0.13	0.06	0.74	0.07
EV	0	0.05	0.06	0.89

Table 10. WTP estimates of each class and relative differences

	WTP values				Relative differences from CV Class		
Attributes	CV	CV+BEV	Serious Interest EV	EV	CV+BEV	Serious Interest EV	EV
BEV					1154	-1002	9936
PHEV					-14448	1438	9177
Energy cost	207	-82*	-435	-1174	-207	-642	-1381
Driving range	45*	628	704	836	628	704	836
All-electric range	-8*	44	-1*	16	44	0	16
Fast charging availability	-119	-32	-15	-20*	87	104	119
Fast charging duration	-89	-76	-81	314	13	8	403
Road tax exemption	5399*	257*	601	-56*	0	601	0
Free public parking	-9045*	-216 *	-156*	-427*	0	0	0
Mobility guarantee	-823	-72*	429	-2063	823	1252	-1240

Note: 1. The unit of currency is euro (€).
2. *: the corresponding taste parameters are non-significant at p<0.10.
3. The values are calculated for the case when the current/stated car costs €15000.
4. In the calculation of relative changes, the values of statistically non-significant coefficients are fixed to 0.
5. Alternative specific constants cannot directly be interpreted as intrinsic preferences for each car type since we used different utility specifications for CV and EV, but we can still compare to see the differences between classes. Therefore, we only provide the values of relative differences for BEV and PHEV.

Although only 6% of strict CV buyers transferred to other classes with higher affinity with EVs, this is a relatively large influx considering the big size of this class. It is also worth noticing that no strict CV buyers became EV buyer: since these two classes can be considered as the ends of the spectrum, it is reasonable that business model itself alone cannot facilitate such a drastic preference change.

The strongest “positive” impact of business models can be found both in classes CV+BEV and serious EV interest: respectively 9% and 7% of each group became EV buyers. The flows between these two classes are around the same in both direction (6% and 7%). This phenomenon demonstrates the effectiveness of business models in strengthening preferences for EV and switching people from buying CVs to EVs. However, 13% of the serious interest class “fell back” to becoming strict CV buyers, while slightly less (9%) of the CV+BEV buyers did.

This “negative” impact of business model is rather unexpected. A closer inspection of these observed choices and individual characteristics of those who “fall back” shows that their reference vehicles are cheaper than average (in all the “fall back” transfer paths, the purchase price coefficients are negative although insignificant) and they mostly change their choices in choice tasks which have EV alternatives of the lowest level of purchase price. Therefore, they might be more price-sensitive than average: they probably chose EV initially if its price difference with CV is small; however, this difference is enlarged in the case of leasing because a lower residue value of EV is reflected in the calculation of monthly payment and leasing EV may be deemed less economic than leasing CV.

As for the EV buyers group, 11% started to consider CV again (fall back to CV+BEV and serious interest in EV class) after leasing is provided. A possible explanation for this phenomenon is that their knowledge for EV is considerably less than those who remained in the same group; therefore, they may initially choose EV for economic reasons without being aware of the low residue value of EV; and later find that leasing EV is not worthwhile in comparison to leasing CV. Similar to the case in strict EV buyers, none of the members belonging to EV buyers fell to the other end of the preference spectrum.

The individual covariates also have significant effect on the transition probabilities, these effects are represented by γ_{jkr}. Because CV buyers and EV buyers both have empty transition paths, we use CV+BEV as the reference class. The parameters for the empty transition paths cannot be estimated thus are not presented.

Many covariates do not reach statistical significance which may be due to the fact the number of observations is too limited for conducting this rather data-intensive analysis. The expected price does not seem to have a strong impact: it is insignificant in all transition paths except for the strict CV buyers; people who expect to buy a more expensive car are less likely to switch to the serious EV interest class. People with more knowledge regarding EV are more likely to switch to other classes if they belonged to CV buyers and have a higher probability to remain in the same class if they were EV buyers.

Attitudes towards leasing can also affect transition probabilities between classes. Since the pro-ownership variable denotes the extent to which one values car ownership, the results imply that a higher attachment to car ownership makes CV buyers more likely to remain in the same class, and for the CV+BEV class it also indicates higher probability of transferring to CV buyers. This is plausible since the transition between classes can only happen if the respondent switch from the initial purchase choice to choosing leasing (of a different type of car) in the second wave of choices; in contrast to people who stayed in CV+BEV class (reference class), those who choose leasing and transferred to other classes are expected to be related to a lower level of pro-ownership. Furthermore, the results related to Pro-EV leasing attitude shows that a higher degree of recognition regarding the suitability of EV to leasing has a positive impact on transferring to serious interest class for CV buyers and remaining in the same class for EV buyers. Finally, the Pro-convenience variable does not have a significant impact on any transition paths.

4.5. Conclusion and discussion

The present study contributes to the literature by exploring the potential of business models in promoting substitution of conventional vehicles by EV. We estimated a discrete choice model to quantify the aggregate impact of providing the potential of leasing, and a latent transition model to investigate its heterogeneous impact on different groups of people. When only battery leasing is provided, the attractiveness of BEV is significantly increased; however, when car lease is also provided for all car types, the effect vanishes and the utility of EV is mostly unaffected or even slightly decreased (in the case of PHEV). The rather insignificant aggregate impact of business model on promoting EV market penetration does not imply that people remain inert. The population can be classified into five classes based on their preferences profiles, and 12.7% of the people switched classes and changed their preference profile under the presence of business models. Around half of these people switched to a class with a higher probability of choosing EV compared to the first wave of choices while the other half transferred in the opposite direction. These two flows likely cancelled each other out and led to the insignificance of the aggregate impact. In general, people who seriously tradeoff between CV and BEV are more likely to be affected by business models and change their preferences. The transition probabilities between classes are also affected by several individual specific variables, including price level of intended car, knowledge of EV and various attitudes towards leasing. These results indicate that in order for business models to fully realize its potential in promoting EV sales, its promotion shall give priority to certain target groups which are more susceptible to business models, and the information regarding the influential individual-specific variables provides us insights for identifying these target groups.

This is the first application of latent transition analysis in studying induced behavioral change and analyzing data from stated choice experiment. Compared to discrete choice models, latent transition analysis extracts in-depth insights regarding behavioral change: it is able to unravel different directions of changes and can also relate the pattern of change with initial preferences. This has practical relevance since it provides a new way of identifying target groups for policy/strategy: it facilitates tailored implementation of policies which can increase efficiency and reduce side effects. Regarding venues for future research, latent transition models can be applied to investigate the behavioral change induced by a wide range of intervention instruments including business strategies and government policies. It has a unique power especially when the induced behavioral change can be in opposite direction for different people. Typical examples are:

- Providing trials for an innovative technology: in the case of EV, more experience gained during trial period is expected to have a positive effect on the perception for EV (Bühler et al., 2014); however, there were also studies found that exposure to EV even enhance people's worries for EV (Jensen et al., 2013).
- Providing travel information: in order to promote travel behavior which is beneficial for the entire system, a social reinforcement strategy can be applied by providing people with information of how many of their peers made the system-beneficial choice; but people who would have taken a detour may stop doing that if they reckon that there is already a sufficient number of people taking the detour.
- Running information campaigns: in order to promote a certain behavior, many governments use campaigns to increase people's knowledge or change their perception. However, this may invoke citizens' doubt regarding the attractiveness of the targeted behavior.

This research has several limitations. First, it only included a fixed price scheme for each battery leasing and car leasing option, which made it impossible to investigate the effect of various pricing schemes for each business model. Second, one may argue that the order of the questions in our choice experiment affects the responses: for each choice task, the respondent makes a choice in the reference context (without business models) and then adapt their choices when different business models are available. Once respondents learn this pattern from the first choice tasks, in later tasks this knowledge may have an impact on their choice in the reference context. An easy adjustment can fix this influence in future research by conducting the experiment in waves: we can let the respondents give the first wave of responses for all choice tasks in the same (reference) context, and then similarly collect a new wave of response for each different context (such as a new policy). Third, the context of the choice experiment is to choose from the three different powertrain versions of the same car model with leasing available for all three alternatives, which is certainly a simplified version of choice options in the real world; it may be also interesting to explore how the consideration of business model trade-off with car types, brands and models when business models are not provided for all cars. Fourth, latent transition analysis requires a large sample because many observations are needed on each transition path especially if the effects of covariates are to be estimated. Many covariates did not reach significance in our analysis which may be a result of the lack of observations in the off-diagonal cells. Finally, due to the question order, we were not able to study the impact of adding battery leasing option when leasing is already available for all car types, which is also a question of high relevance for countries where private leasing is already widespread for all car brands.

Some future research regarding the topic of business models can be suggested. First, the impact of more specifications and types of business models can be explored. In the case of leasing, various pricing schemes can be tested. There are also many different business models in the area of EV apart from leasing and their effectiveness in promoting EV remains unclear. Second, more covariates can be tested in both latent class choice models and latent transition models. It helps to identify members of each class and facilitates making policies and strategies which are class-specific and targeted. This certainly requires a larger sample. Third, the assumption of measurement invariance in latent transition model can be relaxed. The effect of business model or any market instrument can also be forming a new preference profile, which is represented by a new class. In general, there are many research opportunities regarding the topic of business model which can increase our knowledge regarding its potential impact and optimal implementation.

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5. Carsharing: the impact of system characteristics on its potential to replace private car trips and reduce car ownership

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Abstract

This paper aims to explore the potential of carsharing in replacing private car trips and reducing car ownership and how this is affected by its attributes. To that affect, a stated choice experiment is conducted and the data are analyzed by latent class models in order to incorporate preference heterogeneity. The results show that around 40% of car drivers indicated that they are willing to replace some of their private car trips by carsharing, and 20% indicated that they may forego a planned purchase or shed a current car if carsharing becomes available near to them. The results further suggest that people vary significantly with respect to these two stated intentions, and that a higher intention of trip replacement does not necessarily correspond to higher intention of reducing car ownership. Our results also imply that changing the system attributes does not have a substantial impact on people's intention, which suggests that the decision to use carsharing are mainly determined by other factors. Furthermore, deploying electric vehicles in carsharing fleet is

preferred to fossil-fuel cars by some segments of the population, while it has no negative impact for other segments.

5.1. Introduction

Carsharing was introduced a long time ago (its earliest implementation was in the late 1940s) but only gained substantial attention and popularity during the past decade (Becker et al. 2017). Thanks to the widespread use of smartphones, carsharing is becoming increasingly convenient since real time information regarding the availability and location of shared cars can be easily checked via mobile apps. In order to fulfill the diverse demand of consumers, various carsharing schemes are offered in the market, which differ in terms of pricing scheme and ways of organization (one-way vs. roundtrip carsharing). Since carsharing grants people access to cars without the responsibilities and hassles related to car ownership such as regular maintenance and high parking costs, it serves as a viable substitute for conducting car trips and even buying a car for some people. Several empirical studies found that carsharing users reduce their vehicle travel distance and even give up car ownership (Martin et al. 2010; Millard-Ball et al. 2005; Shaheen and Cohen 2013).

The potential of carsharing in reducing car ownership gained considerable attention in automobile industry and policy making. Since each shared car usually can serve more than one person, a carsharing fleet is expected to replace more private cars than the number of shared cars, consequently reducing the total number of cars. Therefore, car manufacturers expect a "reasonable share" of their future profits will be coming from carsharing since car ownership is likely to drop[16], and governments are focused on carsharing's potential in relieving the negative externalities brought by both the production and usage of cars, such as pollution, CO_2 emission, high parking pressure, etc.

In order for (potential) car owners to switch to carsharing and reduce car ownership, the carsharing scheme has to be able to cover some trips which are currently (or expected) conducted by the private car. Duncan (2011) investigated what kind of car trip patterns can be cost-effectively accommodated by carsharing and derive the potential of joining carsharing by calculating the share of people with the compatible trip pattern. A similar study by Schuster et al. (2005) simulated people's choices between owning private car and carsharing by comparing their costs based on the car condition and trip pattern. However, cost may not be the only consideration and people do not necessarily use carsharing to replace private car trips even if it is slightly cheaper. Furthermore, those who can accommodate more trips by carsharing are not necessarily more willing to reduce car ownership.

In order to decide whether there shall be policy incentives for carsharing, the government needs information regarding the scale of impact of carsharing on car ownership. Moreover, in order to understand how this impact can vary for different carsharing systems and individuals, it is also necessary to know what factors affect people's intentions of private car trip replacement and car ownership reduction. Among all potential influential factors, carsharing system service attributes are especially of interest since they are within the control of service providers.

Of all service attributes, the impact of deploying electric shared vehicle is particularly worth investigating. Many governments have been promoting electric vehicles (EV) due to the sustainability target and EVs have also entered carsharing service. If electric vehicles are deployed in the carsharing fleet, the potential benefits of carsharing are further enhanced. For example, many

[16] "VW expects profits from car-sharing and ride-hailing", https://www.ft.com/content/29097c88-1bab-11e7-a266-12672483791a

carsharing users still keep their private car (Martin et al. 2010) and use carsharing services when their car is not available at the ideal time (e.g. because their partner is using the car), a parking place is too hard to find, etc.. In that case, even if those people would not drive less due to carsharing, it can still reduce environmental impacts since most private cars are powered by fossil fuel. Moreover, deploying electric vehicles in shared car fleets provides easier access to electric vehicles (EVs) for many people who still have doubts towards adopting EV as a private vehicle (Zoepf and Keith 2016). People may have less battery-related concerns (replacement costs, life expectancy, possible decrease in range over time) for a shared car compared to a private car they have to purchase, especially if they use shared cars for short urban trips; therefore, a carsharing fleet of EVs may face less resistance from its potential users than the resistance EV has to confront from its potential buyers. From the fleet owners' perspective, EVs may also be a better option because of their lower operational cost and positive environmental image compared to internal combustion engine vehicles. There seems to be a possible synergy of carsharing and electric mobility, therefore it is worthwhile to investigate how deploying electric vehicle would affect potential carsharing users' decision.

The aim of this paper is to investigate the effects of various carsharing system attributes (including car fuel type) on people's choice and propensity of joining and using carsharing. We explore the potential of carsharing in both replacing car trips made by privately owned cars and reducing car ownership. Furthermore, we identify different consumer groups according to their heterogeneous preferences and describe each group based on individual-related variables. Finally, we explore the relationship between people's intention of using carsharing to replace private car trips and the intention of reducing car ownership. For the above purposes, we conducted a stated choice experiment and applied latent class models to analyze preferences and categorize respondents. This paper contributes to the literature by 1) exploring the impact of carsharing system attributes on the intention of replacing private car trips and reducing car ownership under both roundtrip and one-way carsharing schemes, especially the option of deploying electric vehicles in shared car fleet, 2) identifying different customer groups based on their preferences for carsharing and 3) examining the relationship between car owners' intention of private trip replacement and car ownership reduction.

The remainder of this paper is organized as follows: section 2 provides a brief review on relevant literature; section 3 introduces the methodology including survey design, data collection and model estimation. Section 4 elaborates the results we obtained from multiple analyses. The final section provides a discussion regarding the policy implication of the results. Among others, we discuss the implications of our results for the area of shared autonomous vehicles.

5.2. Related work

Most studies on carsharing potential user preferences focus on their decision to enroll as carsharing member, which can be further categorized into three main types. The first type utilizes revealed preference data in the region where carsharing is already available and directly explore the influential factors on people's membership (Becker et al. 2017; Ciari et al. 2015; Juschten et al. 2017). This approach allows the investigation of the impact of those service attributes which differ between carsharing stations or individuals: such as access distance, number of vehicles in each station, etc. (Ciari et al. 2015; Juschten et al. 2017). The second type studies the intention of joining carsharing systems without considering other transport options. The dependent variable is the intention to join carsharing, which is then analyzed by regression models to find individual-related variables that significantly influence the intention to join (Efthymiou et al. 2013; Zhou and Kockelman 2011). These studies focus on the impact of individual characteristics on membership decisions. Since they mostly focus on a single given carsharing system, their models do not capture the marginal effects of carsharing system attributes. The third type mainly uses stated choice experiments to study people's choice between joining carsharing and use other transport options. These experiments consist of several choice tasks that vary the attributes of the carsharing system (and of other transport alternatives). This experimental setting allows the preferences for carsharing system attributes to be captured (Kato et al. 2012; Le Vine et al. 2014b). A recent study of this type is Kim et al. (2017) which explores people's choice between joining a carsharing system, buying a second car and remaining the status quo. A context condition worth noticing in this study is that respondents are assumed to own only one car in the household and have limited access to this vehicle when needed (below 60%) in all choice tasks; however, this may not be the case for many car owners. Despite its valuable contribution, this assumption of a specific context may result in bias when evaluating the general potential of carsharing or even the marginal effects of attributes for the population at large. Besides, this study did not take into account the impact of the fuel type of shared cars. In addition to these three types of studies, (Rotaris and Danielis 2017) applies a rather special approach which uses the generalized cost of carsharing to predict the probability of joining carsharing.

Previous research focusing on the impact of carsharing on car ownership mainly asked current users of carsharing systems to report their (intentions of) ownership change after joining carsharing (Cervero et al. 2007; Firnkorn and Müller 2015; Firnkorn and Müller 2011; Kim et al. 2015; Shankar et al. 2015). (Le Vine and Polak 2017) also estimated a regression model to see what kind of carsharing users are more likely to reduce their car ownership. The effects are usually expressed by how many private cars have been replaced by shared cars. The estimated number of private cars replaced by each shared car is estimated to vary from 2.5 (Douma and Gaug 2009) to 13 (Martin et al. 2010). However, these studies share some common limitations: first, some studies do not compare the car ownership changes of carsharing members with non-members; second, they focus on current carsharing users who are considered to be the early adopters of the service and their behavior may not be representative of the entire potential user group. Therefore, these numbers are likely to be over-optimistic of the effects of carsharing (Tal 2009), which makes it difficult to extrapolate the results to the total population and estimate the total potential of carsharing on car ownership. As an exception, (Klincevicius et al. 2014) used census data to explore the impact of carsharing system on household car ownership.

Few studies investigated what extent carsharing can replace private car trips. An example is Firnkorn & Müller (2011) which asked current car2go[17] users what percentage of current private car trips they plan to replace by car2go, which only provides a descriptive analysis of the intentions of existing users. A much larger share of research investigated people's preferences for carsharing in a short-term mode choice for a given trip, but they only looked at a specific trip context such as commuting (Kim et al. 2017b; de Luca and Di Pace 2014), grocery shopping (Le Vine et al. 2014a) or park & carsharing service (Cartenì et al., 2016); therefore, the results cannot be generalized to assess the total impact of carsharing on replacing private car trips.

Consumer preferences and intentions regarding using carsharing to replace private car trips and reducing car ownership are likely to be heterogeneous since carsharing is a niche market (BCG, 2016) and there may only be a certain group of people who will seriously consider carsharing as an option. Most above studies included various individual-related variables in their

[17] A one-way free-floating carsharing service operated by Daimler.

models to capture their effects on carsharing decisions intentions, but none have attempted to systematically classify people into groups with different preference profiles. As mentioned in the introduction, our current study aims to address all the above identified research gaps.

Finally, the intention of using carsharing to replace private car trips is usually studied separately from the intention of reducing car ownership. As mentioned in the introduction, some previous studies used “the compatibility of current car trip patterns with carsharing” as a proxy for the possibility of switching away from owning car to joining carsharing (Duncan 2011; Schuster et al. 2005). Another somewhat related study is (Le Vine and Polak 2017) which find that among current free-floating carsharing users, those who use the service more often are also more likely to reduce their car ownership. However, to the best of our knowledge, no study attempted to explore whether there is a relationship between the intentions of trip replacement and car ownership reduction.

5.3. Methodology

5.3.1 Data collection and sample

Since we aim to investigate the impact of carsharing on car ownership, it makes sense to narrow the research subjects down to potential consumers of cars. Therefore, our target population is people who have a driver’s license and either own a car or intend to buy a car within the following three years. In addition, we only include respondents whose intended purchase is a new car for private use. People who plan to acquire second-hand cars or company cars are excluded because these decisions may involve different considerations (e.g. company car may not be financed by the user).

We used an existing Dutch national panel (Panelclix) to recruit respondents. These panel members fill out questionnaires on a regular basis for a small reward. The members who are invited to participate in our survey are selected at random from the Panelclix list. Those who choose to participate, first answered a series of filter questions and only people who fit our above requirements were asked to finish the entire survey. The data was collected in June 2016 and the final sample consists of 1003 respondents.

Sample characteristics are listed in Table 1. Comparing our sample to the Dutch car owner data[18], we can see that our sample is fairly representative regarding employment status and age, while being slightly over-represented by females (due to survey distribution quota aiming to reach gender balance among respondents),and people with relatively low income, which shall be taken into account when interpreting the results.

[18] Only 10 people do not have a car right now.

Table 1. Sample characteristics

Variable	Level	Percentage in sample (%)	Percentage in Dutch car owners (%)
Gender	Male	51.7	62.7
	Female	48.3	37.2
Age	<=35 years	25.0	18.9
	36-50 years	24.0	30.2
	51-65 years	30.8	29.8
	>=66 years	19.2	21.1
Monthly net personal income	<1250	17.4	8.8
	1251-2500	49.2	28.6
	>2500	33.4	62.5
Employment status	Paid job	65.9	67.7
	Students	3.6	1.6
	Others	30.5	30.7
Household type*	Single	16.8	22.9
	Couple without children:	40.9	35.5
	Couple with children	31.1	37.5
	Others	11.2	4.1
Education level*	Without high education	56.6	71.1
	With high education	43.4	28.9
Number of cars	0	1.0	
	1	68.4	
	2	27.6	
Access to own car when needed	(Almost) Always:	86.2	
	Most of the time:	9.5	
	Not more than half:	4.3	

*: We cannot find data for Dutch car owners regarding this variable. For household type we used data for the entire Dutch population except children. For education level we used data for Dutch population above 15 years old.

5.3.2 Questionnaire design

5.3.2.1 Survey design

Since we are interested in exploring how individual-related variables affect carsharing preferences and choices, we collected a wide range of information which may be related to decision making of joining and using carsharing. Apart from the basic socio-demographic and socio-economic characteristics, we asked for information related to current car ownership and travel behavior: respondents reported their current state of car ownership and the characteristics of the car they expect to purchase; they were also asked about the frequency of their car trips for each different purpose (including commuting, grocery shopping, other shopping and leisure) and frequency of using public transport and bikes. If the frequency of car trips for a certain purpose is not zero, the respondent is also asked to specify the distance, trip duration and parking time at destination of a typical trip for that purpose.

In addition, we measured their familiarity and attitudes towards carsharing. We first asked their previous experience with carsharing to see whether they have used, seen or heard of carsharing. In total, 6% of the respondents are or have been carsharing members. Considering that 1% of people over 18 years old is estimated to use carsharing in the Netherlands (Harms et al. 2016), carsharing users seem to be overrepresented in our sample, but they still represent a very limited share of all respondents.

In order to measure respondents' attitudes towards carsharing, we presented them with 4 statements about carsharing for which they respond on 5-point Likert scales that runs from (1) totally disagree to (5) totally agree. The seminal work from Bergkvist & Rossiter (2007) showed that if the construct consists of a concrete singular object (in our case being carsharing) and a concrete attribute (attitude for a certain aspect), single items can have the same predictive validity as multiple-item measurements; therefore we can still use it even if the reliability is lower. Taking this into account, in order to capture the attitude of multiple aspects with the least number of statements, the four statements are meant to cover aspects of attitude different from each other.

Table 2 presents the four statements and the distribution of their responses. In general, carsharing does not have a negative image and people do recognize the environmental friendliness of carsharing; however, on average people do not appreciate the convenience brought by carsharing and still have a relatively strong attachment to car ownership. Two statements are found to have high communalities; therefore, we generated a factor "hedonic attitude" from these two statements. The other two statements measure the symbolic and environmental attitude respectively. All factor and item scores are standardized for further use.

Table 2. Statements used for attitude measurement and their responses

Category	Statement	Average score	Standard deviation	Factor loading
Symbolic	Carsharing is for people who cannot afford cars.	2.64	0.834	
Environmental	Carsharing is more environmentally friendly than buying a car.	3.46	0.850	
Hedonic	Carsharing causes more problems than owning a car.	3.31	0.816	0.617
	I like the feeling of owning a car and carsharing cannot match that.	3.77	0.874	0.617

5.3.2.2 Choice experiment design

The main part of the survey is a stated choice experiment which focuses on the decision regarding the frequency of using carsharing and car ownership. As we mentioned in the introduction, carsharing schemes can be categorized into two types, namely roundtrip and one-way. The two most crucial differences between these two types are the following. First, for roundtrip carsharing the shared car always has to be returned to its pick-up point while this is not required for one-way carsharing; Second, roundtrip carsharing allows advanced booking while one-way carsharing does not (booking time up to 30 minutes). We decide to not include both systems in the same choice task since we do not aim to study the competition between roundtrip and one-way carsharing systems; besides, for those respondents who are not that familiar with carsharing, learning about both schemes and trading off between them is rather difficult and may lead to more misunderstanding and errors. Therefore, a separate experiment was constructed for each scheme, and respondents were randomly assigned to only one of the experiments. Before the start of the experiment, respondents were introduced to the basic characteristics of the respective carsharing scheme.

In each choice task, respondents were asked to make a choice between two given alternatives which are a car and a carsharing scheme. The presentation of the car alternative differs depending on the respondents' condition: people who intend to purchase a car in the near future (from now on referred to as *prospective car buyers*) were presented with a car alternative of which the attributes describe the car they expect to purchase. This information is collected from their answers to previous questions in the questionnaire. They were asked whether they are willing to forego the car purchase and use the given carsharing scheme instead. Other respondents (referred to as *car holders*) were only presented the attributes of a carsharing scheme and answer whether they are willing to sign up for the presented carsharing scheme and give up a car which they currently own. At the end of the experiment, these *car holders* filled in the characteristics of their own car (or if they have more than one car, the car which they are most likely to give up) and we assume that this is the car with which they traded off in all choice tasks.

Table 3 lists the attributes that are varied in the experiment and their levels. In the experiment for *prospective car buyers*, the attribute values of the expected car purchase are based on the answers provided by respondents and fixed in all choice sets presented to the respondent. The attributes for carsharing schemes are all varied by three levels except the return location of one-way carsharing, their operationalization is further elaborated below:

- *Fuel type of car*: This attribute is varied in the levels: i) gasoline car, ii) electric car with 100km of driving range and iii) electric car with 200km of range after full charge. This allows investigating preference between gasoline vehicle and electric vehicle with short and medium driving ranges.
- *Purchasing cost*: In case of roundtrip carsharing we set a deposit which is fully refunded after the membership expires, while for one-way carsharing we specify a one-time registration fee. This setting fits the current situation of existing carsharing schemes in the Netherlands.
- *Maintenance cost*: A monthly membership fee is also specified for both carsharing schemes. The values for one-way carsharing are lower than that of roundtrip because current one-way carsharing (such as car2go) do not charge any monthly fee while it is common among roundtrip carsharing schemes.
- *Operating cost:* The structures and levels of operating cost attributes of both carsharing alternatives are based on the price levels of current carsharing schemes in the Netherlands.
- *Access time to the shared car* is also included as an attribute: since the position of shared cars is not fixed at each time of use, the respondents are told that this is an average value.
- *Car availability*: With respect to this attribute we use two different measures for the two carsharing schemes based on their different booking mechanism. Since for roundtrip carsharing it is possible to book a time slot in advance and check when cars are available, the measure we use is the difference between the initial ideal departure time and the closest time slot available. For example, a “15 minutes difference from ideal time” implies that on average a shared car is available only 15 minutes earlier or later than the initial ideal departure time. We only give the average value in order to control the complexity of the experiment. Since one-way carsharing does not allow booking and one can hardly do anything when no car is available (within reasonable walking distance), its availability measure is straightforwardly defined as the probability of a shared car appearing to be able to use when needed.
- *Return location of car*: this attribute only applies to one-way carsharing. It has two levels: 1) reserved parking spots for shared cars: this corresponds to one-way stations-based carsharing for which users have to park the car in the designated spots; 2) reserved parking spots for shared cars + all public parking spots: this level represents free-floating carsharing, which allows users to park the car anywhere allowed.

Table 3. Attributes used in the choice experiment and their levels

Item	Alternative	Attribute	Levels		
Fuel type of car	Buying (holding) a car	Fuel type of expected (current) car	Specified by respondent		
	Both carsharing	Fuel type of shared cars	Gasoline	Electric 100km range	Electric 200km range
Purchase cost	Buying (holding) a car	Price of expected (current) car (€)	Specified by respondent		
	Roundtrip carsharing	Deposit (€)	0	150	300
	One-way carsharing	Registration fee (€)	0	20	40
Maintenance cost	Buying (holding) a car	Cost of expected (current) car (€/month)	Specified by respondent		
	Roundtrip carsharing	Membership cost	0	10	20
	One-way carsharing	Membership cost	0	5	10
Operating cost	Buying (holding) a car	Fuel cost of expected (current) car (€ /km)	Specified by respondent		
	Roundtrip carsharing	Distance cost (€ /km)	0.20	0.25	0.30
		Hourly cost (€)	2	4	6
	One-way carsharing	Minute cost (€)	0.20	0.25	0.30
Access time by walking	Buying (holding) a car	To current parking location (minutes)			
	Both carsharing	To location of shared car(minutes)	2	7	12
Availability of car	Buying (holding) a car	Availability of expected (current) car	Expected: Always available Current: specified by respondent		
	Roundtrip carsharing	Difference from ideal time (minutes)	0	15	30
	One-way carsharing	Availability of shared car (%)	80	90	100
Return location of car	One-way carsharing	Return location of car	Reserved parking spots for shared cars	Reserved parking spots for shared cars + all public parking spots	

In addition to exploring to what extent carsharing can reduce car ownership, we were interested in exploring the potential of carsharing in reducing trips which would otherwise be done by private fossil fuel cars. To that effect, respondents were asked to indicate for each car sharing alternative to what extent they use it to replace their car trips (about which we posed questions earlier in the survey). An answer was given for each of the four different trip purposes using a 5-point scale ranging from 1 “never” to 5 ”for all trips”. An example of a choice task and questions is shown in Figure 1.

	Buying a car	Roundtrip carsharing
Fuel type of the car	Gasoline	**Electric vehicle** with **200km** range
Purchase cost	Price of car: €24000	Deposit: **€300** Fully reimbursed after the membership expires
Monthly maintenance cost	€250 Insurance, repairs, taxes	Membership cost: **€10**
Operating cost	Fuel cost: €0.13/km	**€0.20/km** **+ €4/hr**
Car availability	Alway available	**Available 15 minutes before or after the ideal booking time**
Access time	2 minutes	**4 minutes**

1. If this carsharing scheme is available in your neighbourhood, to what extent will you use it for the car trips of the following purposes?

	None	For a few trips	For around half	For most trips	For all trips
Work/school	◉	○	○	○	○
Grocery shopping	◉	I never make this trip by car			
Shopping (appliances, clothes, etc.)	◉	○	○	○	○
Leisure(visitng family and friends, recreation, etc.)	◉	○	○	○	○

2. If this carsharing system is available in your neighbourhood, will you still make the planned car purchase?

	Yes	No
Your choice	○	◉

Figure 1. An example of stated choice task (text translated from Dutch)

Both choice experiments were created using a D-efficient optimal design (Rose and Bliemer 2009). The priors are mostly based on findings of previous research (Kim et al. 2017a) and assumed when not available. With this input, we used Ngene to construct the two choice experiments and ended up with a 12-choice set design for each, which was blocked into 2 blocks each with 6 tasks to which a respondent was randomly assigned. Hence, every respondent faced 6 choice tasks. In the end, the one-way carsharing experiment had 521 respondents in total while the roundtrip experiment received 482 responses.

5.3.3 Model conceptualization

Corresponding to the two questions in each choice task, we have two dependent variables. The first is an ordinal one measuring the extent to which the respondent is willing to replace private car trips by carsharing. Although in each choice task we collect responses for up to[19] four common trips of different purpose (commuting, grocery shopping, other shopping and leisure), we assume that all influential factors have the same effect on these four responses and use a single model to describe these effects. The second variable is dichotomous and denotes the choice whether to proceed with a planned car purchase (or between keeping or shedding the current car). These two dependent variables are indicators for the latent utility of each level of replacement intensity or each choice.

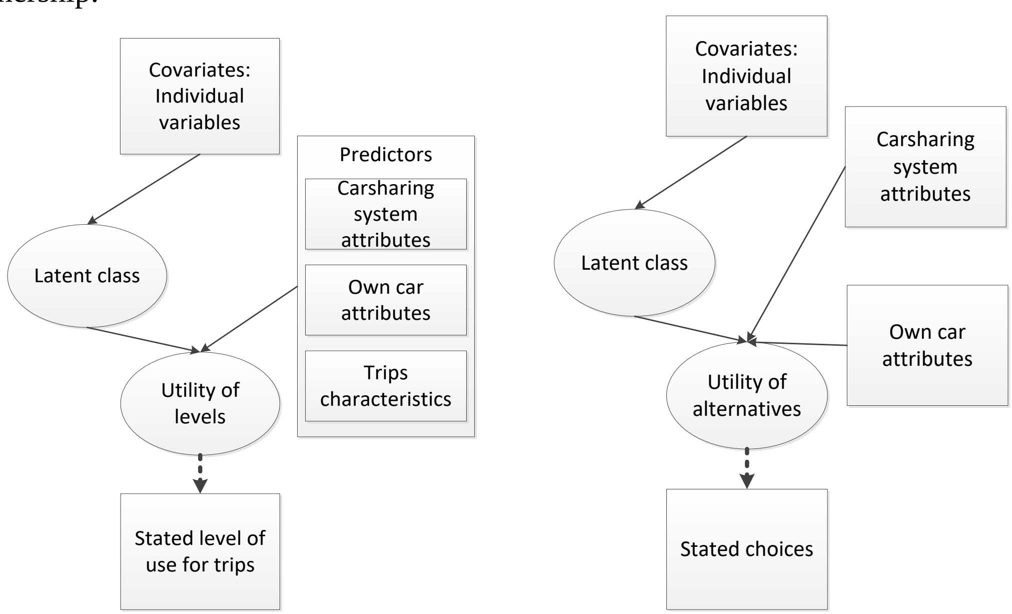
[19] If the respondent previously indicated that s/he never conducts or does not use a car to conduct a certain type of trip, no response is collected for this trip.

Regarding the trip replacement intensity, we explore how its utility is determined by the attributes of both the carsharing system and own car. We have already elaborated upon the carsharing system attributes in section 2.2. The own car attributes we concern are fuel costs and walking distance to the parking location. Utility is also expected to be dependent on the trip characteristics as carsharing may be more feasible and suitable for some trips than others. The characteristics we investigated include trip frequency, duration, staying time at location and the purpose of trip.

As for the choice of car ownership, the utility of choosing carsharing is also assumed to be dependent on the attributes of carsharing system and own car. Although more own car attributes are expected to be influential in this decision: apart from fuel cost and distance to parking location, we also explore the effect of car price, monthly maintenance cost and availability of own car.

The effects of these attributes and factors on utility are expected to be heterogeneous among people. Therefore, we assume that the entire population consists of several classes: these effects are homogeneous within each class and vary between different classes.

Finally, we are also interested in the role individual variables play in determining class membership. In addition to the common socio-economic and socio-demographic variables, we also investigated the influence of frequency of using bikes and public transport and attitudes towards carsharing. Figure 2 is an illustration of the conceptual models for both trip replacement and car ownership.



(a) *(b)*

Figure 2. Model conceptualization: (a) Trip replacement model; (b) Car ownership model

5.3.4 Model specification

We applied latent class models to implement the above conceptualization. To be more specific, we estimated a latent class ordinal regression model for modelling trip replacement and a latent class choice model for the car ownership model.

Let y_{it} denote the response of respondent *i* in choice task *t* and *m* represent a specific category of all possible responses. In the case of trip replacement intensity, *m* can range from never (1) to all (5). In the case of car ownership choice, the respondent can choose either car purchase or carsharing, therefore *m* can take two values. The final stated responses y_{it} are indicators of $\eta_{m|z_{it}}$ which indicates the latent systematic utility of each category (trip replacement intensity) or alternative (car choice) of the response variable for subject *i* in choice task *t*.

In car ownership model, the value of this latent utility has the following form:

$$\eta_{m|\boldsymbol{z_{it}}} = \beta_m + \sum_{k=1}^{K} \beta_{mk} z_{itmk}^{att} + \varepsilon \tag{1}$$

in which β_m and β_{mk} denote the alternative-specific constant and attribute effects respectively. z_{itmk}^{att} represents the value of attribute *k* of alternative *m* in choice task *t* for subject *i*. In latent class models, the entire sample population is assumed to belong to *K* different latent classes which differ in their taste parameters. Therefore, the utility function of members from class x is

$$\eta_{m|x,\boldsymbol{z_{it}}} = \beta_{xm} + \sum_{k=1}^{K} \beta_{xmk} z_{itmk}^{att} + \varepsilon \tag{2}$$

which implies that a different set of β_m and β_{mk}will be estimated for each class *x*. The conditional probability for the response follows the multinomial logit function:

$$P(y_{it} = m|x, \boldsymbol{z_{it}}) = \frac{exp(\eta_{m|x,\boldsymbol{z_{it}}})}{\sum_{m'=1}^{M} exp(\eta_{m'|x,\boldsymbol{z_{it}}})} \tag{3}$$

In the trip replacement model, the dependent variable is of ordinal level and the response probability function is exactly the same as (3) while the "utility" function becomes

$$\eta_{m|x,\boldsymbol{z_{it}}} = \beta_{xm0} + \sum_{q=1}^{Q} m\beta_{xq} z_{itq}^{pred} \tag{4}$$

which applies the function of an adjacent-categories ordinal logit model (Agresti 2002). z_{itq}^{pred} denotes the explanatory exogenous factor *q* which differs between choice tasks. These factors are usually termed as "predictors" in latent class regression models. β_{xm0} and β_{xq} are class-specific intercepts of level *m* and effects of predictor *q* on utility which need to be estimated.

For each subject *i*, the probability of belonging to a class x is predicted by its individual characteristics $\boldsymbol{z_i^{cov}}$ which are termed "covariates". This probability function also takes the form of a multinomial logit model:

$$P(x|\boldsymbol{z_i^{cov}}) = \frac{exp(\gamma_{x0} + \sum_{r=1}^{R} \gamma_{xr} z_{ir}^{cov})}{\sum_{x'=1}^{S} exp(\gamma_{x'0} + \sum_{r=1}^{R} \gamma_{x'r} z_{ir}^{cov})} \tag{5}$$

Hence, for each class an intercept (γ_{x0}) and a set of regression coefficients (γ_{xr}) are estimated. However, some individual-specific variables are dependent on other common covariates (such as socio-economic characteristics) and thus cannot be considered as "truly independent"; in contrast to the active covariates, these variables can be included as "inactive" covariates. The name implies that these covariates do not affect the probability of class membership and are not included in the model estimation. Instead, we calculate the distribution of inactive covariates for each class, which provides a richer profile of different classes. In this study, urban density is included as an inactive covariate.

Finally, the probability of observing a certain sequence of responses can be written as

$$P(\boldsymbol{y_i}) = \sum_{x=1}^{S} P(x|\boldsymbol{z_i^{cov}}) \prod_{t=1}^{T} P(y_{it} = m|x, \boldsymbol{z_{it}}) \tag{6}$$

5.3.5 Model estimation

The latent class regression and the latent class choice model were each estimated separately for one-way and roundtrip carsharing, hence, four models were estimated in total. For the trip replacement model, we pooled and stacked the responses for each of the four trips with different purpose in one dataset in order to estimate a single model for all trips as we mentioned in conceptualization.

We used LatentGold (Vermunt and Magidson, 2013) to estimate all four models. Effects coding was used for all parameters of categorical variables. We used several criteria in order to determine the optimal number of classes: first, statistical measures including ρ2 values and the Bayesian Information Criterion (BIC), which take both model quality and parsimony into account; second, the interpretability of the estimated model, such as the sign and size of coefficients; third, avoid solutions with classes which are not essentially different from other classes; According to all the above criteria, for the latent class ordinal regression model of trip replacement, we arrived at a 3-class structure; and we chose the 2-class solution for the latent class discrete choice model of car ownership.

5.4. Results

This section elaborates the results from the estimated models. We first consecutively present the results of the trip replacement model and the car ownership model; in the end, we discuss the connection between these two choices.

5.4.1 Trip replacement model

5.4.1.1 Consumer groups and preference heterogeneity

Based on their different preferences regarding the frequency of replacing private car trips by carsharing, both in the model for one-way car sharing and the model for roundtrip car sharing, the respondents can be categorized into three classes. Table 4 lists the result of these two latent regression models. Both model fits are quite high and the pseudo R square is significantly improved compared to the one-class ordinal regression model, which demonstrates the power of the latent class model; the prevalence of non-trading behavior (see below for a detailed description) can also be a reason for the high model fit.

We first briefly characterize each of the classes based on their indicated *frequency of use* as presented in the top of Table 5. Class 1 demonstrates an extremely low interest in using car sharing both under one-way and roundtrip car sharing, which can be labeled as “own car oriented”. When answering the questions about the share of their car trips they intend to replace by carsharing, they choose the category ‘none’ for 95% of the time. In contrast, Class 2 intends to replace a larger share of their trips by carsharing and can be described as “CS-leaning”. Class 2 under roundtrip carsharing intends to replace more trips than the same class under one-way car sharing. Finally, Class 3 intends to use carsharing the most for replacing their car trips. They are likely to be frequent users for carsharing and are termed “CS-enthusiasts”. Their responses lean more towards the extremes under roundtrip carsharing; in other words, there are more responses for categories ‘none’, ‘most trips’ and ‘always’. This suggests that in case of roundtrip carsharing, the responses of Class 3 are more divergent across different rating tasks, which implies that the choices are more sensitive to changes in carsharing system attributes and/or different trip characteristics.

As for the size distribution between the three groups, Class 1 is bigger under roundtrip carsharing (63.4%) than under one-way (54.7%), which implies that the latter seems to be capable of attracting more subscribers. Class 3 under one-way carsharing (20.5%) also takes a larger share than under roundtrip (13.9%).

Next, we describe how the trip replacement decisions of the three classes are differently affected by carsharing system attributes, trip characteristics and their current car characteristics. First, we focus on **carsharing system attributes**. The preference for *vehicle type* significantly varies across the three groups. For both roundtrip and one-way carsharing, Class 1 prefers gasoline cars, while Class 3 does not have a significant preference over car types used in carsharing systems. Class 2 prefers gasoline vehicles to EVs with only 100km of driving range under one-way carsharing. However, EVs with 200km range is even slightly preferred to gasoline vehicles, suggesting that a driving range of 200km is sufficient to meet consumer's needs. Under roundtrip carsharing, Class 2 even prefers EVs with 100km range to gasoline vehicles.

The taste parameters for the carsharing attributes *costs*, *availability* and *access time* also differ across the three groups. For Class 1, all parameters have the expected sign and most are statistically significant at a 95% confidence level both under one-way and roundtrip carsharing. On the other hand, for both Class 2 and 3, only *registration cost* or *access time to shared car* have a significant impact. It is worth noticing that the coefficient for *flexible return location* of one-way carsharing is non-significant for all classes, which implies that whether the one-way carsharing system is station-based or free-floating does not seem to influence people's trip replacement decisions. The prevalence of non-significance is probably due to the rather small size of these two predicted classes (especially class 3). Another possible reason is that most system attributes genuinely do not have much impact on trip replacement decisions of these two classes, at least not if the attribute values lie within the range of levels varied in the choice experiment.

Two coefficients for Class 3 which are statistically significant have unexpected signs, namely the membership cost of one-way carsharing and the distance cost of roundtrip carsharing; their size is however rather small in comparison to the constants and other attributes. A possible reason is that a small number of people associate low cost to low quality (we did not specify the quality of the shared cars), despite the fact that we ask respondents to assume the carsharing systems in the experiment are identical apart from the attributes we describe. Since Class 3 is rather insensitive towards costs (all other cost attributes are non-significant), these people may prefer a higher quality system. Hence, they may think it is represented by high cost, which may explain the positive cost parameter. In general, the parameter estimates of Class 3 in our model are not conclusive and shall not be overly interpreted since the predicted class size is small. If we wish to obtain accurate parameter values for this class, it is advisable to collect a larger sample or over-recruit people who have strong intention to replace private car trips by carsharing.

Trip characteristics, including *trip purpose*, *frequency*, *duration* and *staying time at destination* all influence the trip replacement decisions. Under one-way carsharing, their impacts are vastly different between Class 2 and 3. Class 3 tends to use carsharing more to replace trips which are more frequent, less than 1 hour and require a longer stay at the destination, while this is the opposite for Class 2. Furthermore, Class 3 mostly tends replace more grocery shopping trips, while Class 2 is willing to replace more shopping and leisure trips. Under roundtrip carsharing, both Class 2 and 3 tend to replace more trips which last between 16-30 minutes and when the stay at the destination is less than an hour. Class 2 also replaces more frequent trips while there is no clear preference for Class 3.

It is worth mentioning that the parameter estimates cannot be directly contrasted with the normal usage pattern of current carsharing systems. For example, a typical roundtrip carsharing trip mostly has a parking time around 3 hours; while our model shows that Class 3 prefer parking time of less than 1 hour the most, which may seem contradictory. However, the parameter estimates are class-specific and relative, while the revealed pattern is also related to the distribution of trip characteristics among the population. Parking time between 2-4 hours is not significantly preferred by Class 3, but Class 3 members conduct significantly more trips with 2-to-4-hour parking time (compared to trips with other parking duration), therefore this may still end up with a peak pattern of 3-hour parking time even if there is no relative preference between trips with different parking time. In addition, each trip’s utility score is a combination of the coefficients of all its characteristics (duration, frequency, etc.). Most of these trips also have a trip duration of less than 5 minutes which has a large negative coefficient, therefore these trips turn out to be less preferred.

The **characteristics of the current car** also have a significant impact on the intensity of trip replacement. As expected, under both one-way and roundtrip carsharing, most groups tend to use carsharing more to replace their car trips if they currently (or are expected to) have higher fuel cost or a longer parking distance.

Table 4. Parameters and z-values of the latent class ordinal regression model regarding choice of trip replacement

	Oneway Class 1: Own car oriented		Class 2: CS-leaning		Class 3: CS-enthusiast		Roundtrip Class 1: Own car oriented		Class 2: CS-leaning		Class 3: CS-enthusiast	
	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value
Intercept												
None	6.1689	4.0617	1.1168	2.0873	-2.0747	-3.1032	0.4248	0.6012	0.0606	0.1200	-0.5451	-1.4350
A few trips	2.6668	3.4142	1.4202	5.2418	0.6273	1.9241	-0.7403	-2.0981	1.9085	7.3766	-1.2773	-5.9175
Half of trips	1.0804	5.7120	0.2165	4.0588	1.6205	27.4439	-0.7636	-5.3700	1.8126	26.8875	-0.0036	-0.0540
Most trips	-2.0645	-2.6348	-0.5262	-1.9368	0.4459	1.3649	-0.2936	-0.7159	-0.2477	-0.9642	0.9968	5.1607
All trips	-7.8516	-4.9611	-2.2274	-4.0845	-0.6190	-0.9579	1.3727	1.9305	-3.5339	-6.6522	0.8292	2.2073
Predictors												
Gasoline car	0.1078	1.2823	0.0414	1.4205	0.0160	0.4549	0.2012	3.1487	-0.1684	-3.5631	0.0315	0.9007
EV with 100km range	-0.0110	-0.1382	-0.1198	-3.7935	0.0037	0.1008	-0.1674	-2.4641	0.2234	4.7212	-0.1127	-3.0056
EV with 200km range	-0.0967	-0.9827	0.0784	2.5975	-0.0197	-0.5656	-0.0338	-0.5495	-0.0550	-1.2391	0.0812	2.3566
Registration fee	-0.0137	-3.6595	-0.0044	-3.1988	-0.0015	-0.9183						
Deposit							-0.0003	-1.0692	-0.0002	-0.8651	-0.0003	-1.5235
Membership cost	-0.1013	-6.6516	-0.0006	-0.1147	0.0164	2.7399	-0.0301	-5.3611	-0.0007	-0.1810	-0.0004	-0.1303
Minute cost	-5.4655	-3.2077	0.0420	0.0804	-0.2501	-0.4097						
Distance cost/km							-1.8365	-1.6389	-0.7780	-0.9769	1.3296	2.2146
Hour cost							-0.1161	-4.1294	-0.0195	-1.0607	0.0096	0.7443
Availability	2.1669	3.0179	0.2839	1.1437	0.1459	0.4830						
Difference from ideal time							-0.0167	-4.9704	0.0013	0.4917	-0.0012	-0.6069
Access time	-0.0501	-3.1288	-0.0233	-4.3191	0.0061	0.9592	-0.0652	-6.0483	0.0073	0.8620	-0.0187	-3.1484
Flexible return location	-0.0011	-0.0091	0.0434	1.0361	-0.0051	-0.1020						
Trip Frequency												
Once a month or less	0.0474	0.4053	0.0072	0.1474	-0.2945	-4.1457	-0.0171	-0.1552	-0.4588	-6.0288	-0.1338	-2.4368
2-3 times per month	-0.1804	-1.3593	-0.0788	-1.6402	-0.0859	-1.4973	0.1965	2.2537	-0.4052	-5.9421	-0.0262	-0.5621
1-2 times per week	-0.0572	-0.5540	-0.0061	-0.1371	0.1943	4.4169	0.3047	3.8054	-0.1394	-2.4563	-0.0027	-0.0671
3-4 times per week	0.2878	2.5014	-0.0591	-1.0134	-0.0353	-0.5967	0.2500	2.6275	0.4233	5.4545	0.0860	1.6080
5 times per week or more	-0.0976	-0.5625	0.1368	1.5168	0.2214	3.6273	-0.7342	-3.3210	0.5801	6.3311	0.0767	1.2101
Trip duration												
5 minutes or less	0.1019	0.6652	-0.3671	-5.4117	0.0418	0.6468	-0.4250	-3.2544	-0.0140	-0.1636	-0.3944	-5.8414
6 - 15 minutes	0.0278	0.2613	-0.2567	-6.0551	0.1164	2.4803	-0.1639	-1.9971	0.0911	1.4743	0.0953	2.3107
16 - 30 minutes	-0.0717	-0.7030	0.1588	4.1041	0.0220	0.4378	0.0733	1.0191	0.1529	2.5248	0.0887	1.9909
0.5-1 hour	0.0687	0.6277	-0.0288	-0.5580	0.1151	1.9672	0.1902	2.2425	0.1033	1.2863	0.0456	0.8266
More than 1 hour	-0.1267	-0.7970	0.4938	7.4362	-0.2952	-3.4819	0.3253	3.2754	-0.3333	-3.0532	0.1648	2.2497
Stay time at destination												
Less than 1 hour	-0.0279	-0.1918	0.4039	7.2866	-0.4337	-7.6581	-0.0683	-0.6167	0.2912	4.4694	0.1154	2.1640
1 -2 hour	-0.0366	-0.3514	-0.0576	-1.4699	-0.0888	-1.9581	-0.0542	-0.7067	-0.0109	-0.1904	-0.0915	-2.2997
2.1 - 4 hour	-0.1311	-1.2444	-0.1276	-3.2853	0.0968	2.1078	0.0030	0.0403	-0.1588	-2.8565	0.0439	1.0501
More than 4 hours	0.1955	1.4315	-0.2187	-3.7882	0.4258	7.5235	0.1194	1.3138	-0.1215	-1.6638	-0.0678	-1.2967
Purpose												
Commuting	-0.1617	-1.0942	-0.1883	-2.7894	-0.1154	-2.0038	-0.2351	-2.0664	-0.2998	-3.9339	-0.2401	-4.2650
Grocery shopping	-0.2925	-2.0712	-0.3547	-6.7061	0.2315	4.6349	0.1895	1.8146	-0.2037	-3.0274	0.0725	1.4435
Shopping	0.0669	0.5710	0.1874	4.2895	-0.0568	-1.1622	0.0231	0.2837	0.1591	2.5287	0.0519	1.1482
Leisure	0.3873	3.9913	0.3556	8.7694	-0.0593	-1.2499	0.0226	0.3121	0.3444	5.9160	0.1158	2.6312
Fuel cost per km	0.7860	1.3119	0.3276	1.0417	1.3371	6.5150	-2.3798	-3.4516	3.9435	10.4177	-3.6562	-12.1785
Parking distance	0.1272	14.6152	0.0696	10.1080	-0.0359	-8.3331	0.0360	2.8963	-0.0015	-0.1956	0.0304	6.2414
Pseudo R-squared		0.6866					0.6835					
Pseudo R-squared without latent class		0.0708					0.0458					

Table 5. The within-class distributions of choices and covariates of the trip replacement model

	One-way						Roundtrip					
	Own car	CS-leaning	CS-enthusiast				Own car	CS-leaning	CS-enthusiast			
Frequency of use												
None	95%	30%	1%				95%	6%	19%			
A few trips	3%	41%	15%				4%	38%	6%			
Half of trips	1%	15%	49%				1%	45%	15%			
Most trips	1%	10%	22%				0%	10%	34%			
All trips	0%	4%	13%				0%	1%	26%			
Mean	1.07	2.18	3.30				1.07	2.61	3.41			
Covariates				Wald	p-value					Wald	p-value	
Gender				1.0	0.600	-				0.0	0.990	-
Male	52%	56%	56%				49%	54%	50%			
Female	48%	44%	44%				51%	46%	50%			
Age				10.4	0.006	**				20.0	<0.001	**
Mean	50.02	50.41	42.92				51.38	45.77	49.86			
Education				7.3	0.120	-				21.1	<0.001	**
Low	23%	21%	23%				19%	26%	17%			
Middle	36%	36%	32%				38%	35%	18%			
High	40%	43%	46%				42%	39%	65%			
Income				7.0	0.130	-				9.1	0.058	*
Low	19%	20%	12%				16%	17%	17%			
Middle	51%	47%	49%				53%	42%	41%			
High	30%	33%	39%				30%	41%	42%			
Household				14.9	0.021	**				18.5	0.005	**
Single	19%	17%	14%				19%	6%	19%			
Couple without kids	44%	38%	28%				45%	41%	36%			
Single or couple with kids	32%	34%	51%				29%	48%	44%			
Others	5%	11%	6%				7%	6%	1%			
Employment status				13.2	0.040	**				13.0	0.043	**
Employed	62%	67%	83%				63%	67%	68%			
Student	3%	5%	2%				4%	4%	1%			
Retired	21%	22%	9%				22%	20%	19%			
Others	14%	5%	7%				11%	9%	11%			
New purchase planned				8.6	0.014	**				4.3	0.120	-
Yes	74%	80%	91%				74%	83%	84%			
No	26%	20%	9%				26%	17%	16%			
Frequency of using public transport				23.9	0.047	**				25.6	0.029	*
(Almost) Everyday	1%	5%	3%				1%	1%	4%			
1-6 days per week	11%	20%	26%				9%	20%	19%			
Less than once per week	88%	75%	71%				90%	79%	76%			
Frequency of using bikes				20.1	0.130	-				14.9	0.380	-
(Almost) Everyday	20%	26%	11%				21%	31%	25%			
1-6 days per week	38%	40%	51%				35%	35%	41%			
Less than once per week	42%	34%	38%				44%	34%	33%			
Symbolic attitude				5.2	0.073	*				14.2	0.001	**
Mean	-0.04	-0.04	0.12				-0.08	0.20	0.11			
Environmental attitude				3.1	0.210	-				5.8	0.055	*
Mean	-0.02	0.09	-0.23				0.03	-0.12	0.35			
Hedonic attitude				32.4	<0.001	**				21.9	<0.001	**
Mean	0.25	-0.20	-0.42				0.14	-0.42	0.06			
Urban Density (Inactive)												
Rural	33%	40%	37%				33%	33%	25%			
Small city	50%	44%	46%				52%	50%	54%			
Big city	17%	17%	17%				15%	17%	21%			

Note: **:significant at p<0.05 *: significant at p<0.1 -: not significant

5.4.1.2 Personal characteristics

The class membership model reveals the impact of personal characteristics on class membership. Table 5 displays the individual variables included in the model and their Wald statistics and p-value. The within-class percentage distribution of each individual covariate is also presented.

Class 3 has the largest share of people who are younger, highly educated, earning high income, employed, have kids and use public transport more often under both one-way and roundtrip carsharing (a couple of effects are not statistically significant though). By contrast, the composition of Class 1 is mostly opposite to Class 3 in terms of these individual characteristics. In other words, the covariate distribution of Class 1 and 3 lie on different ends of the spectrum. For example, with respect to employment status, Class 3 have the highest percentage of employed people while Class 1 have the lowest. Consequently, the covariate distribution of the Class 2 mostly lies between Class 1 and 3. The only exceptions are age and educational level: under roundtrip carsharing Class 2 is the youngest and least educated; on the other hand, under one-way carsharing it is the oldest. There is no significant difference in the distribution of gender and urban density across the three groups.

Since Class 2 and 3 indicate their intention to use carsharing and are likely to enroll for carsharing membership, we can contrast their characteristics to the previous findings in carsharing members. We confirm the typical image of CS users: younger than average, well-educated, have higher income, employed and more likely to have children (Becker et al. 2017; Le Vine and Polak 2017). Becker et al. (2017) also found that people who are employed tend to use one-way carsharing more frequently: although there is no discernible different between Class 2 and 3 regarding the employment status for roundtrip carsharing, we do find that under one-way carsharing Class 3 has a much higher percentage of employed people than Class 2. Finally, while most studies find carsharing members are predominantly male (Becker et al. 2017; Juschten et al. 2017 and its citations), we do not find any significant impact of gender on the intention of trip replacement.

We now focus on the impact of *attitude* on class membership. All three attitudes have a significant influence in case of roundtrip carsharing, while only symbolic and hedonic attitude are relevant under one-way carsharing. Surprisingly, the average attitude is not always congruent with the preferences of every group. In the model of one-way carsharing, while Class 3 has the highest preference for carsharing, they attach a more negative symbolic value to carsharing compared to the other two groups. This counter-intuitive result suggests that this negative connotation is not strong enough to deter Class 3 away from using carsharing. Under roundtrip carsharing, Class 2 recognizes the environmental-friendliness of carsharing the least while they intend to replace more trips than Class 1, which suggests that the replacement is not motivated by environmental considerations.

5.4.1.3 Discussion

The impact of carsharing system attributes on the intended frequency of private car trip replacement is rather limited according to our model. For Class 1, although all coefficients are significant, group members choose to never use carsharing to replace their private car trips in 95% of their responses to trip replacement questions. Therefore, the effect of promoting carsharing usage is expected to be rather limited for this class if the performance of carsharing systems is not drastically increased (beyond the range we tested). For the other two classes, only *shared car type*, *registration cost* and *average access time* to shared car are significant predictors. A previous study based on an existing carsharing system also finds that the distance to carsharing stations is a significant determinant of carsharing membership (Juschten et al.

2017). In general, most attributes regarding costs and availability of car do not have a significant impact on trip replacement decisions.

We mentioned above that the preference for car type differs for Class 2 in two schemes: for one-way carsharing EV with 200km range is their favorite, while for roundtrip carsharing EV with only 100km range is already preferred over gasoline vehicle. This may be explained by the characteristics of the trips for which they prefer to use carsharing. Under roundtrip carsharing, Class 2 uses it more for trips of middle length (16-30 minutes), for which 100km range is less likely to be a problem; on the other hand, they use it mostly for longer (more than 1 hour) trips under one-way carsharing and 200km seems to be sufficient to meet their requirements.

Different classes also vary in terms of their attitudes towards carsharing and how their own car characteristics affects their willingness to use carsharing in replacement of private car. These coefficients may reveal the respondents' motivation of using carsharing. For example, under one-way carsharing, Class 2 members who currently have higher fuel costs intend to use carsharing to replace more trips, which is probably motivated by saving operation cost of car trips.

Apart from the socio-demographic variables and attitudes, we also examined the trip patterns of each class in order to explore whether those who show higher intention have a trip pattern more "compatible" with carsharing. The trip characteristic distributions of all classes are almost identical. For roundtrip carsharing, Class 3 only stands out with the highest share of trips with parking time between 2-4 hours (29.4% vs. average of 26.4%), which matches the typical trip pattern of each carsharing system. Class 3 of one-way carsharing has the highest share of frequent trips (at least 3 times per week, 33.5% vs. average of 24.5%), this demonstrates that the flexibility of one-way carsharing makes them more suitable for accommodating frequent trips such as commuting. In general, it seems that Class 3 does not have any distinct trip pattern which can explain their high intention of trip replacement.

5.4.2 Car ownership model

This section looks at people's choice regarding whether they will use carsharing to replace their expected car purchase or current car. Table 6 presents the estimated choice model and Table 7 presents the distributions of covariates within each class. We found that a two-class model structure best describes the behavior. We first estimate a full model, and in the final model we constrain those parameters which are not significantly different across classes to be equal. The final model fit is high and the improvement from basic multinomial logit model is also significant. However, since most attributes are non-significant, the model fit is mostly contributed by the constants. This is mainly caused by non-trading behavior which will be discussed later in detail.

For both one-way and roundtrip carsharing, Class 1 and 2 are labeled as "Ownership-Oriented" and "CS-Oriented" according to their choice patterns. The choice responses are rather extreme for both classes: when answering whether to obtain or give up ownership of a current (or intended) car if carsharing becomes available, Class 1 choose to keep the car or go through the planned car purchase in over 97% of responses, while Class 2 opt for carsharing and forego the planned car purchase or replace one of their current cars in the vast majority (over 70% for one-way carsharing and 85% for roundtrip) of choice tasks. This implies that non-trading behavior is prevalent in the sample. Some research suggests that these observations shall be discarded (Hess et al. 2010) which can improve model fit (Wardman and Ibáñez 2012); however, it can be an expression of genuine preferences (Börjesson et al. 2012): given the attribute range in choice experiment design, when none of the other alternatives are more attractive than the alternative which the respondent sticks to, non-trading behavior is observed.

Table 6. Parameters and z-values of the latent class discrete choice model regarding choice of car ownership

	One-way				Roundtrip			
	Ownership-oriented		CS-oriented		Ownership-oriented		CS-oriented	
	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value
Alternative specific constant								
Buy car	0		0		0		0	
Carsharing	**-5.0970**	-4.0945	1.3890	1.2209	-1.2586	-1.4300	**2.1376**	4.6842
Attributes								
Gasoline car	0.1709	1.4110	0.1709	1.4110	0.0615	0.3990	0.0615	0.399
EV with 100km range	-0.1334	-1.0610	-0.1334	-1.0610	-0.0467	-0.2952	-0.0467	-0.2952
EV with 200km range	-0.0375	-0.3088	-0.0375	-0.3088	-0.0148	-0.0999	-0.0148	-0.0999
Registration fee	**-0.0130**	-2.3194	**-0.0130**	-2.3194				
Deposit					-0.0004	-0.6359	-0.0004	-0.6359
Membership cost	-0.0010	-0.0516	-0.001	-0.0516	**-0.0443**	-2.5986	0.0219	1.2260
Minute cost	2.6725	1.2711	2.6725	1.2711				
Distance cost/km					-0.7843	-0.3159	-0.7843	-0.3159
Hour cost					-0.0842	-1.3943	-0.0842	-1.3943
Availability	0.7878	0.7706	0.7878	0.7706				
Difference from ideal time					**-0.0295**	-2.7693	0.0086	0.7470
Access time	**-0.1703**	-2.6912	-0.0208	-0.8580	**-0.1115**	-3.0738	0.0144	0.4104
Flexible return location	0.0177	0.1077	0.0177	0.1077				
Current/Expected car characteristics								
Car price	0.0162	1.1668	**-0.0471**	-4.2881	-0.0032	-0.3117	**-0.0191**	-3.4387
Fuel cost	0.3208	0.1386	-0.6997	-0.9110	0.0105	0.3134	**-0.1114**	-2.6893
Parking distance	**0.2334**	8.4361	**-0.0515**	-3.7330	2.0985	1.4541	**5.4214**	2.8559
Maintenance cost	**-0.0024**	-3.2154	-0.0003	-0.4654	-0.0024	-1.5916	-0.0008	-0.7355
Log-Likelihood	-730				-674			
Null Log-likelihood	-2166				-2004			
McFadden Rho-square	0.663				0.664			
Log-likelihood of MNL	-1407				-1336			

Comparing the two models, Class 1 takes a dominant share in both models (78.3% and 82.5%); while Class 2 of one-way carsharing (21.7%) is slightly larger in size than that of roundtrip carsharing (17.5%). The model results therefore suggest that the potential of both types of carsharing in reducing car ownership is on par with each other.

We now briefly discuss the taste parameter for service attributes. The fuel type of the shared car does not have any significant impact on the final choice for both classes under both one-way and roundtrip carsharing. Except for the registration fee of one-way carsharing, none of the taste parameters for carsharing system attributes are significant for Class 2, while access time is significant for Class 1 both for roundtrip and one-way carsharing. In addition, monthly membership cost and car availability also have significant impact under roundtrip carsharing. Similar to the trip replacement model, these non-significant parameters may be a true reflection of people’s preferences: when considering whether to use carsharing and forego a planned car purchase (or shed an owned car), carsharing system attributes genuinely do not play an important role as long as they are not extremely high or low. It may also be explained by two other reasons: first, Class 1 hardly trade-off between attributes across choice tasks; second, the size of Class 2 is limited.

All variables with respect to the current (or expected) car (car price, fuel cost, maintenance cost and access time to one’s own car) are significant for at least one class in the model for one-way or roundtrip carsharing. This implies that these factors influence the decision regarding whether to use carsharing and reduce car ownership. For Class 2 in both models, people who (are expected to) have a more expensive car are less likely to forego their ownership: this suggests that an expensive car may be more than a tool for transport and bears a symbolic value, which was revealed by previous studies (Steg 2005).

Table 7. The within-class distributions of choices and covariates of the car ownership model

	One-way Ownership -oriented	CS-oriented				Roundtrip Ownership-oriented	CS-oriented			
Choice										
Buy the car	98%	28%				97%	14%			
Give up purchase	2%	72%				3%	86%			
Covariates			**Wald**	**p-value**				**Wald**	**p-value**	
Gender			0.6	0.430	-			0.3	0.610	-
Male	52%	60%				50%	51%			
Female	48%	40%				50%	49%			
Age			7.0	0.008	**			1.5	0.220	-
Mean	49.91	44.25				50.40	47.63			
Education			3.8	0.150	-			3.6	0.170	-
Low	23%	20%				21%	20%			
Middle	36%	32%				33%	42%			
High	40%	48%				46%	38%			
Income			2.0	0.360	-			4.1	0.130	-
Low	18%	18%				17%	17%			
Middle	50%	47%				50%	44%			
High	32%	35%				33%	40%			
Household			5.8	0.120	-			1.6	0.650	-
Single	19%	13%				17%	15%			
Couple without kids	41%	31%				41%	48%			
Single or couple with kids	34%	47%				35%	32%			
Others	6%	9%				6%	6%			
Employment status			6.2	0.1	*			7.3	0.064	*
Employed	66%	73%				62%	73%			
Student	3%	6%				4%	1%			
Retired	20%	14%				22%	16%			
Others	11%	7%				11%	10%			
New purchase planned			14.3	<0.001	**			4.8	0.03	**
Yes	75%	92%				76%	85%			
No	25%	8%				24%	15%			
Frequency of commuting trip by car			11.7	0.069	*			9.7	0.140	-
5 times per week or more	30%	33%				29%	27%			
1-4 times per week	27%	34%				30%	34%			
Less than once per week	9%	8%				6%	7%			
None	34%	25%				35%	31%			
Frequency of using public transport			12.4	0.086	*			6.2	0.520	-
(Almost) Everyday	2%	3%				2%	2%			
1-6 days per week	14%	26%				12%	16%			
Less than once per week	84%	72%				87%	82%			
Frequency of using bikes			8.7	0.270	-			20.0	0.006	**
(Almost) Everyday	21%	15%				21%	38%			
1-6 days per week	39%	47%				40%	16%			
Less than once per week	40%	38%				38%	46%			
Symbolic attitude			0.4	0.510	-			1.1	0.220	-
Mean	0.01	-0.10				0.00	0.04			
Environmental attitude			1.3	0.250	-			0.2	0.640	-
Mean	0.02	-0.22				0.05	0.01			
Hedonic attitude			13.2	<0.001	**			8.5	0.004	**
Mean	0.10	-0.34				0.06	-0.30			
Urban Density (Inactive)										
Rural area	36%	35%				32%	31%			
Small city	48%	44%				51%	55%			
Big city	16%	21%				17%	14%			

Several socio-economic variables account for preference heterogeneity. Both under roundtrip and one-way carsharing, employed people are more likely to be a member of Class 2. Under one-way carsharing, Class 2 is also younger. Gender, education, household composition, income are non-significant predictors for class membership in both models. There is no significant difference between the two classes regarding urban density distribution either. Although higher education and higher income can lead to a higher possibility to join and use carsharing, they are also found to have positive impact on the probability to maintain car ownership (Le Vine and Polak 2017), which may explain why their effects in our model become non-significant. In contrast, (Le Vine and Polak 2017) also found that people with children are more likely to join carsharing and reduce car ownership: although our Class 2 under one-way carsharing still has a much larger share of people with children, we do not find this strengthened impact. Under both one-way and roundtrip carsharing, people who are expected to buy a new car have a higher probability of belonging to Class 2 than those who do not. This was expected since the potential buyers are asked whether they will forego the planned purchase while the others answer whether they will shed a current car. It is certainly easier to give up a purchase which has not been materialized than giving up a car one already owns.

People's travel patterns also have substantial influence on class membership. Class 2 has more frequent public transport users under one-way carsharing and contains more intensive bike users under roundtrip carsharing. This suggests that a multi-modal person is more likely to forego car ownership when carsharing becomes available.

Of the three attitudinal items, only the hedonic attitude has a significant effect on class membership, which shows that the decision of giving up car ownership is influenced by the individual's attachment to car ownership, while one's perception regarding the environmental friendliness and symbolic image of carsharing do not have much impact.

5.4.3 Relation between the trip replacement and car ownership decisions

A main motivation for car ownership is to conduct trips by car. If carsharing becomes available and can also fulfill this functional use of car ownership, it is likely to reduce the need for car ownership. Therefore, a plausible conjecture is that the intention of reducing car ownership is related to people's willingness to replace their private car trips by carsharing. In electric vehicle adoption research, several studies assume that the acceptance of EV is strongly related to the inconvenience caused by EV which stems from the mismatch of the limited driving range of EV and the travel pattern (such as long trips) of individuals (Tamor et al. 2015; Tamor et al. 2013). Similarly, as we mentioned in the introduction, there have been previous research effort to measure the potential of carsharing by calculating how many people's current travel patterns are economically compatible with carsharing (Duncan 2011; Schuster et al. 2005): the inherent assumption is that the choice of giving up car ownership depends on the extent to which carsharing can cover (replace) one's current trips. In this section, we aim to investigate whether people who intend to use carsharing to replace more of their private car trips are more willing to give away (one of) their car.

We assign each respondent to a class in both classifications (trip replacement and car ownership) according to the posterior probabilities of belong to a particular class based on their responses and individual characteristics, and explore whether there is any relation between these two class memberships. Table 8 and 9 display the cross tables of people's membership under the two classifications for one-way and roundtrip carsharing. We can derive some interesting insights from the two tables:

1) Some people who choose carsharing to replace very few of their car trips are still willing to give up their car ownership, albeit the share is rather small (10% of the total sample). A possible explanation for this may be that only a small share of the current car trips absolutely needs to be done by driving; with the support of carsharing in fulfilling this essential need, this group can shed a car and turn to other travel modes such as biking or public transport to conduct the trips which were previously conducted by private car. This group therefore may correspond to those carsharing users who reduced their mileage of car trips after joining carsharing scheme and give up their car (Millard-Ball et al. 2005).

2) In the case of one-way carsharing, the preference regarding trip replacement is in line with their preference for giving up car ownership: CS-enthusiasts has the largest percentage

which are CS-oriented than other two groups. (Le Vine and Polak 2017) also found that those who use free-floating carsharing more are also more likely to reduce their car ownership.

3) In the model of roundtrip carsharing, the percentage of CS-enthusiasts (Class 3 in the trip replacement decision) who are also CS-oriented (Class 2 in the car ownership decision) is lower than CS-leaning (Class 2 in the trip replacement decision). This may seem surprising since CS-enthusiasts on average are willing to use carsharing to replace more of their private car trips than CS-leaning. However, in Table 5 we can see that the CS-leaning class of roundtrip carsharing has the lowest hedonic score which indicates their low attachment to their own car compared to the other two groups. This shows that the decision of reducing car ownership does not solely depend on the practical consideration such as how many current trips can the carsharing scheme serve. Other factors may override the importance of the practicalities, such as emotions and attachment towards car ownership.

Table 8. The distribution within the two classifications for one-way carsharing

Car model class	*Trip model class*	*Own-car oriented*	*CS-leaning*	*CS-enthusiasts*	*Class size*
Ownership-oriented	% within Trip model class	91.6%	70.5%	54.2%	78.2%
CS-oriented	% within Trip model class	8.5%	29.5%	45.8%	21.8%
Class size	% of Total	54.7%	24.8%	20.5%	100.0%

Table 9. The distribution within the two classifications for roundtrip carsharing

Car model class	*Trip model class*	*Own-car oriented*	*CS-leaning*	*CS-enthusiasts*	*Car class size*
Onwership-oriented	% within Trip model class	89.5%	67.0%	76.1%	82.5%
CS-oriented	% within Trip model class	10.5%	33.0%	23.9%	17.5%
Trip Class size	% of Total	63.4%	22.7%	13.9%	100.0%

It is expected that one-way free-floating carsharing is the most popular scheme due to its flexibility comparing to one-way station-based and roundtrip carsharing. Our results show that indeed a larger group of car drivers is interested in using one-way carsharing for some of their car trips compared to roundtrip; however, one-way carsharing does not show significantly higher potential in reducing car ownership. The relation between usage intensity and car ownership reduction is also different for the two types of carsharing systems. Furthermore, the perks of free-floating carsharing - free parking at all public parking spots - do not show any effect on the probability of joining or using carsharing. We expect carsharing (especially one-way) is most likely to be operated within big cities with a certain level of urban density to be profitable. People living in highly urbanized areas may also have a higher interest in carsharing due to the limited parking and expensive parking fee in these areas. However, we discerned no significant difference in the overall preferences for carsharing between people living in areas with different levels of urban density (the urban density level variable is non-significant in the membership function).

5.5. Conclusions and discussions

5.5.1 Conclusion

This study aims to investigate car drivers' intention of replacing private car trips by carsharing and reducing car ownership when a carsharing scheme is available, which shed light on the potential of carsharing among all car drivers. Latent class models are estimated to identify groups with different preference profiles. We found that for both intentions of trip replacement and car ownership reduction, people vary significantly with respect to their preferences for carsharing in general, its system attributes and how the characteristics of their own car affect their preferences. In total around 40% of the entire sample (CS-leaning and CS-enthusiasts) indicate that they may be willing to use carsharing to replace at least some of their private car trips. About 20% (CS-oriented) are likely to give up a planned car purchase or shed a current car when a suitable carsharing system becomes available. These numbers can be regarded as an upper limit of the potential for carsharing in replacing private car trips and reducing car ownership since models calibrated by stated preference data tend to overrate the preference for new products (see section 5.3). This variance of preference may be attributed to the difference in socio-economic condition, travel pattern and carsharing-related attitudes, confirming similar findings in previous studies.

We also examined the impact of carsharing system attributes on these two intentions. As for the fuel type of the shared cars, it does not make any difference in the decision of giving up car ownership. Regarding the trip replacement decision, EVs are even preferred to gasoline vehicles by some classes; however, EVs with limited range is less preferred when carsharing is mostly used for long trips, but a driving range of 200km is enough to compensate in this case. Based on these findings we may conclude that consumers in general do not show resistance and even demonstrate preference for electric vehicles. Regarding other system attributes such as costs and availability, if the current performance level is already acceptable (within the range of our experiment), a further improvement of the system performance in these aspects do not seem to have a significant impact on facilitating carsharing to replace car ownership or private car trips.

As for the relation between the decision of trip replacement and forgoing car ownership, people who use carsharing to replace more trips are not necessarily more willing to give up their car, which indicates that these two effects of carsharing must be studied separately. By looking at the two decisions together, we arrive at a more detailed classification of the population and a richer picture of people's preference profiles regarding carsharing. We reveal groups such as heavy carsharing users who still want the guarantee of their own car and people who are willing to give up their car even when carsharing cannot replace most of their car trips (which they may conduct by other travel modes instead).

5.5.2 Policy implications

We can derive several policy implications from the findings. First, our study reveals that the potential for car sharing is quite large: as explained above 40% of the entire sample indicate that they may be willing to use carsharing to replace at least some of their private car trips, and 20% are likely to give up a planned car purchase or shed a current car when a suitable carsharing system becomes available. This implies that policies stimulating car sharing can have substantial societal relevant advantages, related to owning and using cars, as explained in the introduction. Policies to stimulate car sharing can, for example, be the provision of designated parking facilities (pull) but also the introduction of more paid parking in residential areas (push). Secondly, deploying electric vehicles has no negative or even slightly positive impact on increasing carsharing use, which confirms the potential of carsharing in reducing car trip emissions. This not only is relevant because shared vehicles can be EVs reducing the environmental pressure of car use, but it is also relevant because an increase in EV sales in the fleets of shared vehicles can stimulate EV sales in the entire car fleet, because due to scale effects (more sales) prices of EVs will go down, and the relatively high purchase costs are a barrier for many people to buy an EV (Liao et al. 2017). Thirdly, the potential of CS to reduce car ownership reduces the environmental impact of car ownership - note that producing cars also results in environmental pressure. And parking pressure can to some extent be reduced via increased levels of sharing. So, policies that stimulate CS might have environmental benefits via reduced ownerhip levels. Fourth, for one-way carsharing systems, in contrast to station-based setting, free-floating setting usually require much more government cooperation since it demands access to public parking spots. However, our results suggest that consumers do not really appreciate the extra flexibility brought by free-floating. This suggests that a station-based one-way carsharing system (such as Autolib in Paris) is a better option which is easier to implement and does not reduce utility for its users. Fifth, reducing user costs or increasing the availability of shared cars seem to have little or no impact on mid-term decisions such as the extent of replacing private car trips and reducing car ownership. Therefore, these strategies are probably not useful if the goal is to facilitate more trip replacement and car ownership reduction. Sixth, our results reveal that potential consumers' preferences regarding carsharing are highly heterogeneous. Certain groups have more favorable attitudes and preferences towards carsharing and may be more susceptible to carsharing promotion policies/strategies, thus it is recommended that they are given higher priority in such promotion. Furthermore, since the groups which intend to use carsharing to replace more private car trips do not necessarily overlap with the group which is more willing to reduce car ownership, campaigns and advertisements promoting carsharing should choose target groups depending on their specific goal. Seventh, because our study shows that young people are more than average inclined to become users of CS systems, such systems may lead to postponed car ownership, or even to an overall reduction of the desirability of owning a car, as debated in the literature on 'peak car' (Goodwin and van Dender 2013).

5.5.3 Limitations and recommendations for research

This study has several limitations. First, since carsharing is still a niche market, despite the fact that we collected a sample of average size, the number of respondents who are potentially interested in carsharing is rather limited; we also observed the prevalence of non-trading behavior among the general population. This may lead to statistical insignificance of some attributes, predictors and covariates. If we wish to have better estimates of the preference coefficients of the potentially interested group in order to fine tune the carsharing scheme services, we need a sample which is more targeted towards the potentially interested customers. However, this was not the main aim of this study, which was to examine the potential of carsharing among the general population of car drivers. Second, stated preference method is known to result in inflated willingness-to-pay for some socially desirable behaviors (Axsen et al. 2015), and the online survey we used for data collection is known to result in even more positive responses than other types of surveys such as face-to-face interviews (Efthymiou and Antoniou 2016). Therefore, our results may be over-optimistic in evaluating the potential of carsharing. Thus, while we find that the carsharing potential is rather limited in the general car driver population, it may even be more limited than we find here. Third, in this explorative study we simplified some aspects of the choice problems: for example, we did not consider the uncertainty of remaining range when someone takes an electric shared car with limited range. Neither did we consider more flexible pricing structure (such as different price for driving and parking). Finally, a large part of our respondents resides in rural areas. Although they seem to have no significant difference in terms of the intention of trip replacement and car ownership reduction and a fair share of them seem to be quite positive towards carsharing, it shall be kept in mind that some of the service attribute levels we used in the experiment are not economically feasible to be realized in those areas.

More future research is needed in order to better investigate people's preferences and the possible benefits of all types of carsharing. Comparing the usage pattern of roundtrip and one-way carsharing is an interesting direction which is of high practical relevance. For example, if one-way carsharing scheme is especially often used for shopping trips, then the carsharing scheme can set up more stations (parking docks) around shopping centers. The potential of peer-to-peer (P2P) carsharing in rural area is also worth investigating: our results show that people living in rural area seem to be as interested in carsharing as people from urban areas; however, as we mentioned in the limitations, the carsharing systems in our experiment may not be feasible or profitable in rural area and P2P carsharing may be the only option. Therefore, it is important to examine people's preference for P2P carsharing. Furthermore, if we wish to arrive at a more realistic forecast of the potential of carsharing, we may combine revealed preference data with stated choice data in the model estimation. Finally, the introduction of shared autonomous vehicles will also further complicate or even completely change the entire picture. Many researcher, planners and policy makers now envision a prospect in which car ownership is vastly reduced because people on a large scale will make use of shared autonomous cars. However, our results pose doubt on this prospect: most people prefer to remain owning a car and only intend to make limited use of carsharing to replace their trips, and this preference is not very sensitive to improvements of carsharing systems. It is more likely that as long as cars are affordable and parking regulations with respect to car parking do not dramatically change, people will continue to own and use private cars even when shared autonomous cars become available on a large scale. Therefore, more behavioral research is needed to investigate the feasibility and possibility of the rosy future scenario promised by the introduction of shared autonomous vehicles.

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6. Conclusion

This thesis aimed to explore the role business models play in electric vehicle adoption. It first reviewed the existing research on consumer preferences for electric vehicles (chapter 2). Two studies were conducted to investigate consumer preferences for leasing in the context of EV adoption (chapter 3) and explore the impact of leasing on electric vehicle adoption (chapter 4). Finally, a next study addressed the potential of carsharing in replacing private car trips and reducing car ownership and how do system characteristics influence this potential (chapter 5). Below we present the results of the thesis as answers to the research questions per chapter.

6.1 Conclusions for Study 1: Literature review of consumer preferences for electric vehicles

- *How are EV preference studies conducted (methodology, modelling techniques and experiment design)?*
- *What attributes do consumers prefer when they choose among specific vehicles?*
- *To what extent do these preferences show heterogeneity? What factors may account for heterogeneity?*
- *What research gaps can be derived from the review and what recommendations can we give for future research?*

Most EV preference/adoption studies took either the economic or psychological approach. The vast majority adopted the former approach since its framework allows to investigate the impact of both vehicle attributes and individual characteristics on EV preference. We summarized a range of vehicle attributes which are found to be significant for vehicle type choice regarding the financial and technical attributes, such as purchase price, fuel cost, driving range and vehicle performances. In the case of EV, the condition of charging infrastructure and government incentives are also crucial. The preferences for these attributes and EV in general are generally heterogeneous and can indeed be at least partly explained by individual-specific variables. We also identified multiple research gaps which can be considered for future research, of which the most relevant gap to our following studies is that previous studies overlooked the potential role of business models in boosting EV adoption.

6.2 Conclusions for Study 2: Consumer preferences for innovative business models in electric vehicle adoption

- *Which business models do consumers prefer (for different types of vehicles)?*
- *How do people's attitudes influence their preference?*

Our study showed that when all three business models are available, vehicle leasing is the most popular option while battery leasing is the least popular for BEV. However, full price purchase is preferred to vehicle leasing in the case of CV and PHEV. This does imply that vehicle leasing has added value for BEV, and battery leasing may only be appealing for a rather small group. It is worth noticing that unlike the case of full availability of business model options, for BEV battery leasing is actually preferred to buying when only battery leasing and buying are available. Since our data collection precluded the possibility of actual preference reversal, this "reversal" of preference on the aggregate level is the result of many who chose battery leasing in the second wave switching to vehicle leasing in the final wave[20]. Our results also suggest that attitudes do have a significant influence on the preference for business models.

6.3 Conclusions for Study 3: The impact of business models on electric vehicle adoption: a latent transition analysis approach

- *What is the aggregate impact of business models on EV preferences?*
- *How can consumers be classified based on their preferences for electric vehicles?*
- *How does the provision of business models affect EV adoption of different groups of consumers?*

The results of the discrete choice model imply that the attractiveness of BEV is significantly increased when battery leasing is offered on top of buying; however, when vehicle leasing is also provided for all car types, this effect vanishes for BEV and the preference for PHEV even slightly decreases. In both cases the aggregate impacts are rather small. However, there are more changes of preferences than the discrete choice model suggests. Applying the latent transition analysis, we uncovered that around 6% of the population became more likely to choose EV while another 6% switched their choices in an opposite direction. These two flows likely cancelled each other out and led to a rather infinitesimal aggregate impact. The probability of switching not only depends on one's initial preferences for EVs but also individual-specific variables.

6.4 Conclusions for Study 4: The impact of carsharing system characteristics on its potential to replace private car trips and reduce car ownership

- *What is the impact of carsharing system attributes (especially the option of deploying electric vehicles in shared car fleet) on the intention of replacing private car trips and reducing car ownership?*

[20] This point was not included in the chapter since I prefer to include the published article in its original form.

- *How can consumers be classified based on their preferences for carsharing?*
- *Is there any relation between car owners' intention of private trip replacement and car ownership reduction?*

For both the intentions of trip replacement and car ownership reduction, the impact of carsharing system attributes is heterogeneous among the population. We found that in general the fuel type of shared cars does not make any difference in the decision of reducing car ownership; BEVs are even preferred to CVs by some categories of consumers in terms of the decision of replacing private car trips. This result suggests that people do not have resistance towards electric shared-cars and some even prefer it to CV. Other carsharing system attributes do not have much impact on the intention of using carsharing to replace private car trips or reducing car ownership. As for the deployment of electric vehicles.

As for the relation between the decision of trip replacement and reducing car ownership, the possibility of giving up car ownership does not monotonously increase with the intention to replace private car trips, since our analysis show that people who intent to use carsharing to replace more trips are not necessarily more willing to give up their car.

6.5 Policy and strategy implications

The first and foremost insight derived from our results for policy making is to take alternative business models into account when making policies aiming at promoting EV adoption and eventually phase out fossil-fuel cars. In case of leasing, some straightforward policy options worth considering are applying planned/existing financial incentives for EV purchase to leasing as well and raise the awareness for leasing in EV campaigns. The amount of financial incentive can differ according to the fuel type and business model, which results in multiple policy portfolio options. Since the preferences for leasing differ in case of BEV and PHEV and our scenario analysis showed that subsidizing PHEV may even crowd out the market share of BEV, the selection of the optimal policy portfolio depends on whether the policy goal is to promote all EVs in general or only zero-emission vehicles such as BEV. The distinction between PHEV and BEV is especially crucial in areas where PHEVs are mostly driven under gasoline mode.

As for carsharing, even without shifting to a full EV fleet it already has the potential to reduce car ownership, thereby alleviating the environmental impacts of car production and other problems such as parking pressure. Deploying EVs in the carsharing fleet not only further enhances the contribution in emission/pollution reduction of carsharing, but also stimulates EV sales in the entire market since it provides easy access/trial to EVs which may in turn increase EV adoption and prices of EVs will go down due to scale effects (more sales). Since our studies show that deploying electric vehicles has no negative or even slightly positive impact on the potential of carsharing in replacing private car trips and reducing car ownership, implementing incentives for EV deployment in the carsharing fleets is expected to have positive synergy effects.

Finally, as self-driving technology is fast developing and it is expected to be combined with carsharing/ridesharing (Fagnant and Kockelman, 2015), in the future we may witness a full transition from private vehicles to autonomous shared taxis, in which case the decision of vehicle type would be mainly made by fleet owners instead of individual consumers. Governments are suggested to also prepare for this scenario and balance the effort spent between incentivizing private car consumers and fleet owners.

Our results can also provide valuable insights for multiple stakeholders in the industry, including car manufacturers, lease companies and carsharing systems. In order to attract consumers and increase satisfaction, car manufacturers can consider providing alternative business models for certain car types when it has added value. They can also reduce the searching cost for business models via methods such as introducing it along with the car models or issuing campaigns which increase awareness for those who are most likely to benefit from it. Since many car manufacturers are having problems with meeting the CO2 emission standards or EV sale quotas of some governments, alternative business models or value adding services may also be utilized to achieve these targets. Last but not least, car manufacturers may also account for the evolution of business models (from ownership-based to access-based) when making long term strategy planning.

As for companies which are directly providing these alternative business models such as leasing companies and carsharing companies, our studies provide a detailed profile of people's preferences for these business models, this knowledge can be useful in estimating the business potential of these business models and also identifying what are the key attributes which affect people's preferences.

As a general point for all decision makers, since consumer preferences are heterogeneous in almost all cases, policies and strategies will achieve higher efficiency if they can identify the target group which is most susceptible to these policies/strategies. For example, introducing leasing to those who would seriously trade-off between BEV and CV may push them towards choosing BEV, while it is unlikely to have the same effect for someone who considers PHEV. Our analyses provide insights regarding the various variables which can be used in classification or identifying target consumers: apart from the common socio-demographics, attitude and initial preference (when only buying is available) for car types can also have an influence.

6.6 Reflections

As I mentioned in the introduction, there is an omission in knowledge of the roles played by business models in EV adoption research in the transportation field. Moreover, this omission actually is more general since most research tends to focus on the 'hard" attributes such as technology and the accompanying infrastructure but tend to ignore the process through which the adoption takes place. For a product to end up with a consumer, it happens in the market via commercialization which will pass several stakeholders and procedures along the way and each of these steps can affect the final adoption. For example, dealerships play a crucial role in car purchase and they are not the most enthusiastic towards EVs, hence dealerships and the pre-existing retail structure may also be hindrances for EV diffusion (Cahill et al., 2014). If we do not disentangle and investigate the impact of business models in research, it would be impossible to find out how much of the low sales of EVs shall actually be attributes to the limitations of the traditional business model instead of the limitations of technology, and the expected results derived from these researches probably cannot be translated into reality. In this respect, the main contribution of this thesis is providing a quantitative analysis of consumer preferences for business models and their impacts on promoting EV adoption.

Study 3 found that leasing has no significant impact on the choice of fuel type on the aggregate level, despite that leasing is preferred to purchase in case of BEV. Although a small group of people did switch their preference profile under different business models, more than 80% were still unaffected. A possible reason is that the sample was unfamiliar with the leasing option and tend to stick with what they know21: the data collection was conducted in 2016 when private leasing was still largely unknown for most people. As private leasing becomes more popular, its positive impact on EV adoption is expected to grow stronger.

[21] Stated choice experiments usually suffer from hypothetical bias, namely that people choose the new alternative more than they tend to in real life: however, this effect may be stronger with alternatives which may have implications for social desirability, such as "organic" "green" etc. (Alfnes, Yue and Jensen, 2010)

In retrospective, if there would have been more time and funding which would allow multiple data collections, I would have included more variations of the business models. One example is to investigate the car type preference when only vehicle leasing is available. This would be close to the case of company car in the Netherlands (Koetse and Hoen, 2014). I could have also tested the impact of leasing attributes such as monthly premiums by varying their values in the experiment. These additions would allow us to more thoroughly depict the impact of business models under different settings.

I did not explicitly discuss the impact of preferred car type on the choice for fuel type since it is not statistically significant; however, this can be a crucial factor which leads to the current low market share of EVs. Because the gas price was rather steady and at a low level in the past years, consumers' interest in heavier vehicles such as SUVs surged: in 2017 the market share of SUVs in the US is 43% in contrast to 26% of sedans[22], while the percentage of SUV in Europe is 29.4% which is an almost 20% increase compared to 2016[23]. However, most electric cars in the market are sedans and most currently available electric SUVs are in the luxury segment. Possible reasons for this are that SUVs are heavier and require even bigger batteries which push the price too high, or that car manufacturers think SUV buyers may not like EVs. Electric SUVs only take 7% of the entire BEV market[24], which is much lower than percentage of EVs in the total market. The combination of an increasing group of SUV buyers and the lack of electric SUV models in the market can have a negative impact on EV adoption. Since I did not find any discernible differences regarding EV preferences between small car and SUV buyers, this suggests that there is a demand for non-luxury electric SUVs models waiting to be fulfilled by car manufacturers.

6.6.1 Motivation for EV adoption – a consumer perspective

In a typical stated choice experiment of EV preference, EVs perform worse on basically every attribute except fuel cost. When we are trying to identify and quantify the "barriers" for EV adoption, the underlying assumption is that adopting EV is a desirable end goal for consumers: they genuinely "want" EVs but they are either not capable to adopt or are uncertain whether the downsides would overshadow the benefits. A question which is rarely asked in the preference studies is why people want EVs in the first place or whether they want an EV at all. Since fossil fuel powered vehicles are the absolute default or status quo which do not require justification, everyone who considers adopting EV is likely to have a rather explicit and "active" reason or motivation. Adopting an EV is probably not a goal in itself; instead, potential customers may have (multiple) higher-level goal(s) and they think adopting EV is possibly a better means to achieve the(se) goal(s) than CV. Therefore, the strength of EV purchase motivation hinges on the importance of the relevant goals and whether adopting EV is indispensable in achieving these goals. Previous literature has identified several motivations/goals for EV adoption including being environmental friendly, saving money and obtaining higher vehicle performance. When the motivation is strong, consumers will actively seek the benefits of EV, be less sensitive towards the "barriers" and even cooperate in mitigating these barriers (such as coming up with ways of adapting to charging). Take Norway as an example: this is the only exception in the world where EVs are cheaper than comparable gasoline cars thanks to the generous tax break (Ecofys, 2018). Given this money-saving possibility, the market share of EV is higher than gasoline cars even though the public charging infrastructure is far from ideal: only 2% of the EV users rely on public slow charging on a daily

[22] https://www.cbsnews.com/news/suvs-are-running-sedans-off-the-american-roads/
[23] https://www.jato.com/global-domination-suvs-continues-2017/
[24] https://insideevs.com/electric-car-sales-western-europe/

basis (Mathieu, 2018), and charging points are mostly concentrated in big cities which makes driving in rural area problematic25. Therefore, I think the task of helping to reduce barriers for those who wish to buy EV is essentially different from persuading non-believers that EVs are “not necessarily worse”: for example, the leasing model is probably mostly effective for those who are already interested in EV but have slight doubts or financial burden. This point stresses the importance of identifying the potential consumers for EV adoption at the current stage.

6.6.2 Motivation for EV promotion – a governmental perspective

Applying the same “motivation analysis” to governments, the goals they try to achieve with electric vehicle adoption are mainly reducing air pollution and cutting greenhouse gas emission. The question which is rarely asked here is whether promoting EV adoption is the most effective way of achieving these goals. Moreover, since most EV promotion policies are notoriously expensive (especially the purchase incentives), it is worth investigating whether the specific EV promotion policies are cost-efficient in meeting these “ultimate” goals compared with other types of policies. Previous research found that tax incentives for EV are rather costly for reducing the environmental externalities of road transport (Yan, 2018). However, this inefficiency may be justified as the incentives are regarded as long-term policies for breaking market barriers of innovative technologies which are indispensable.

Policies only focusing on increasing the number of EV adoption may even have negative impacts for the ultimate goals of reducing pollution and emission. Again in Norway’s case, 70% of the Norwegian EV Association members have a fossil-fuel car and EV is only their second car which is used to escape tolls26. Furthermore, some people even switched from public transportation, bikes and carsharing back to buying electric car since it is cheaper compared to a fossil fuel car27. Some EV promotion policies therefore may have resulted in higher car sales which eventually increases emission due to more car production. This is not to doubt the necessity of substituting fossil fuel cars by electric vehicles as a long term goal, but more as a reminder that the stress shall be “substituting fossil fuel cars” instead of “the more the merrier”.

6.7 Future research directions

In each separate chapter we have already include several venues for future research in the conclusion section which will not be repeated here. We will add several other recommendations in this section.

As a further extension to the analysis in chapter 4, the latent transition analysis can also be applied on the choice of business models. This analysis would allow us to answer the following questions such as: what patterns emerge regarding the chosen combination of car types and business models? Do people who prefer battery leasing to buying switch to vehicle leasing when it also becomes available? In other words, are battery leasing and vehicle leasing competitive or complements with each other in terms of BEV adoption? What are the prominent characteristics of the group which prefer leasing BEV? What was their initial choices of car type and business model when vehicle leasing was not available?

Another valuable topic is to carefully inspect each step in the process of vehicle adoption and identify what are the crucial factors or barriers in the adoption process apart from the product itself, such as the difficulties in accessing accurate information regarding EV and

[25] https://www.nytimes.com/2018/01/04/business/energy-environment/norway-electric-hybrid-cars.html
[26] https://www.theguardian.com/money/2018/jul/02/norway-electric-cars-subsidies-fossil-fuel
[27] https://www.nytimes.com/2015/10/17/business/international/norway-is-global-model-for-encouraging-sales-of-electric-cars.html?rref=collection%2Ftimestopic%2FElectric%20and%20Hybrid%20Vehicles

charging, encountering non-cooperative dealers, etc. This would initially require a qualitative approach such as focus groups or in-depth interview which sample from both EV owners and potential EV adopters (who are seriously considering and at least once undertook measures to explore EV). After the possible factors are identified, quantitative analysis can be conducted to examine their size of influence. As active stakeholders in the vehicle sales process, sales agents and dealerships are acting non-cooperative towards selling EVs for a wide range of reasons, which include extra learning cost to familiarize with EV technology28, reduced commission due to a longer persuasion process in the case of EV29, and the lower expected maintenance cost of EV30. If their effects are found to be non-trivial, it may be an important negligence of our current EV promotion incentives to ignore dealership.

Finally, we should always adopt a dynamic perspective. Just as how the market value of technology depends on the business models, people's attitudes and preferences for business models are also depending on and evolve with time and technology development. For example, when fully autonomous vehicles come into being, it will basically eradicate the difference between carsharing and ride-hailing/ridesharing. People's preference for these two business models may change drastically as autonomous vehicles become powerful and mainstream.

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[28] https://www.ipsos.com/en-us/news-polls/rda-finds-us-dealerships-not-prepared-ev-invasion
[29] https://www.nytimes.com/2015/12/01/science/electric-car-auto-dealers.html
[30] https://www.autonews.com/article/20171218/RETAIL05/171219906/electric-vehicles-and-the-future-of-fixed-ops

Summary

Background

Road transport heavily relies on fossil fuels and contributes to a series of problems including pollution, greenhouse gas emissions and fuel dependence. Replacing fossil-fuel powered vehicles with electric vehicles (EV) on a large scale is regarded as a potential or even necessary solution to alleviate these problems. Therefore, many national governments have announced a ban on sales of new fossil fuel cars by 2030/40. In order to achieve this goal, they also implemented incentive policies for EV adoption. However, the market share of EVs remains low in the vast majority of countries despite the governmental promotion.

In order to achieve the goal of phasing out fossil fuel powered cars, it is of utmost importance to understand consumer preferences for EV and the main barriers for mass adoption, which can facilitate the development of more effective policy instruments. The most prominent barriers towards EV adoption are mainly due to the limitations of state-of-the-art battery technology (such as expensive batteries, limited driving range, rather long charging times and uncertainties surrounding battery lifetime and residual value) and the lagging behind of charging infrastructure development. Since most of these barriers can be attributed to the battery technology, a fundamental way to overcome these barriers in the long run is to finance the R&D of battery technology which eventually increases the competence of EV. However, an often-ignored notion is that the value of the technology itself is not inherent nor fixed, and we can already attempt to boost the value of the technology and overcome some of the barriers in the meantime.

Importance of business models

The value of technology depends on the way in which it is commercialized, which is usually termed as "business model". The two basic components of business models which are relevant to consumers are value proposition which is the product or service provided by the company; and the revenue model which means the way in which the company charges its customers (Bohnsack et al. 2014; Kley et al. 2011). Take the most common business model in the car

market for example: the value proposition is the full ownership of a car, and the revenue model is an upfront payment of the purchase price.

Since battery technology at its current stage entails a barrier for widespread market penetration, existing mainstream business models may be insufficient to address these barriers. Deploying the same technology via different business models can lead to different economic outcomes (Chesbrough 2010). In the case of EV, both leasing and carsharing can relieve financial burden brought by initial purchase price; they also reduce the uncertainties by shifting some risks away from consumers, such as battery technology becoming obsolete or residual price being unexpectedly low when trading at the second-hand market. Therefore, applying alternative business models may help in increasing EV penetration or even be the prerequisite for EV to be commercially viable. In fact, almost 80% of the BEVs in the US are currently leased instead of bought while only 30% of the cars are leased for the entire fleet[31], which implies that the share of leasing is much higher for EV than for Conventional Vehicles (CV). In order to explore the potential of business models in increasing EV adoption, we need to conduct empirical studies to understand their impact on EV adoption.

Research Gap

There has been a myriad of studies concerning consumer preferences for electric vehicles in the transportation field. Most applied the stated preference approach and focused on the attributes of the vehicles and the accompanying charging infrastructure. Another strand of literature mainly looked into the influence of psychological factors on EV preference. However, almost none of these studies explicitly mentioned the business model for adoption[32], which makes it impossible to disentangle and measure the impact of business model.

On the other hand, there are some studies coming from the management field that explored the impact of business models combined with sustainable technologies including EVs (Kley et al. 2011; Budde Christensen et al. 2012; Wells 2013; Bohnsack et al. 2014). Being explorative in nature, most of these studies either introduced a conceptual framework, discussed the possible impacts of business models in theory or conducted case studies. To the best of my knowledge, there have been no quantitative empirical studies which can give us insights regarding the pattern and size of the impact of business models.

Research Goal

To summarize, so far there have been no empirical studies conducted to quantitively study the consumer preference for alternative business models and how they can influence electric vehicle adoption. Therefore, the main goal of this thesis is to gain insight into consumer preferences for different business models in the context of electric vehicles and explore the impact of providing alternative business models on EV market share. The business models I choose to focus on include battery leasing, vehicle leasing and carsharing. As mentioned earlier, given that many countries have mandated the complete phasing out of fossil fuel cars, effective and efficient incentives for EV are needed to break the market barriers and achieve the target. This research can derive insights which inform the decision making of EV promotion policies and thus has high societal relevance.

Outline of the thesis

The thesis first starts with a literature review of studies on consumer preferences for electric vehicles in order to synthesize the existing findings which contributes to studies on EV adoption in general. Two empirical studies are then devoted to the business model of battery leasing and vehicle leasing. In the third chapter I investigate the choice of business model together with the choice of car type, which gives us insight into consumer preferences for these two business

[31] https://www.bloomberg.com/news/articles/2018-01-03/why-most-electric-cars-are-leased-not-owned

[32] See (Valeri & Danielis 2015; Glerum et al. 2014) for two exceptions.

models. However, even if leasing would be most preferred for BEV, this does not necessarily mean that offering more EV leasing options would lead to an increase in BEV sales; because the results of this study make clear that those who prefer leasing may choose BEV anyway even when only buying is available. Therefore, chapter four is dedicated to exploring how the availability of alternative business models influences the choice of fuel type and in turn the market share of EV. Chapter five looks at the business model of carsharing and studies whether the deployment of electric shared cars can influence the decision of carsharing usage and car ownership. The findings of the studies are summarized below.

Theories and methods

For all models applied to describe choice behavior in the empirical studies, the underlying theory is random utility maximization (RUM), which states that individual always chooses the alternative with the highest utility, while this utility is the sum of two components, namely a systematic utility based on the attributes of the alternative and a random “error” which is unknown to researcher. It is the dominant theory in the field of travel behavior modeling and more details can be found in Train (2003).

As for the specific models, I mainly applied advanced discrete choice models including mixed logit and hybrid choice model. Latent transition analysis was also used when studying behavioral change. All model estimations are based on the same dataset which was collected in June 2016 via a survey among all potential car buyers in the Netherlands. The final sample size is 1003 respondents.

Findings

Study 1: Literature review of consumer preferences for electric vehicles (Chapter 2)

In this chapter, a literature review is conducted regarding the studies on consumer preference for electric vehicle in order to have a full picture of the state-of-the-art on EV preference research and to identify the gaps. The vast majority of studies on disaggregate EV preferences adopted the economic approach since its framework allows to investigate the impact of both vehicle attributes and individual characteristics on EV preference. I summarized a range of vehicle attributes which are found to be significant for vehicle type choice including the financial and technical attributes, such as purchase price, fuel cost, driving range, vehicle performances. In the case of EV, the condition of charging infrastructure and government incentives are also crucial. The preferences for these attributes and EV in general are generally heterogeneous, and the heterogeneity can be at least partly explained by a range of individual-specific variables including socio-demographics, psychological factors, spatial factors, mobility and car-related conditions, experience with EV and social influence. Multiple research gaps are identified, of which the most relevant gap to our following studies is that previous studies overlooked the potential role of business models in boosting EV adoption.

Study 2: Consumer preferences for innovative business models in electric vehicle adoption (Chapter 3)

This study investigates consumer preferences for business models in the context of electric vehicle adoption. I focus on the business model of battery leasing and vehicle leasing. In this study, the choice of business model is viewed as an extra decision made together with the choice of fuel type. Since leasing complements with the shortcomings of certain technologies (such as full battery electric vehicle), the rank of preference for leasing may differ depending on the choice of vehicle type. Furthermore, I also tested the relation between people’s attitudes towards leasing and their preference order for leasing.

The study showed that when all three business models are available, vehicle leasing is the most popular option while battery leasing is the least popular for BEV. This does imply that vehicle leasing has added value for BEV, and battery leasing may only be appealing for a rather small group. However, full price purchase is preferred to vehicle leasing in the case of CV and

PHEV, which implies that the preference for business models varies for different fuel types as expected. Our results also suggest that attitudes do have a significant influence on the preference for business models. Higher appreciation for the convenience of leasing leads to higher probability of choosing vehicle leasing for all three car types. On the other hand, people who appreciate car ownership are less likely to choose vehicle leasing. Moreover, those who believe that EVs are more suitable for leasing than conventional vehicles are more likely to adopt BEV via battery and vehicle leasing, while it does not have a significant impact on the probability of leasing PHEV.

Study 3: The impact of business models on electric vehicle adoption: a latent transition analysis approach (Chapter 4)

This study takes a rather different perspective from Study 2: instead of focusing on the choice of business models, study 3 looks at the choice of car type and aims to explore how the availability of business models influences this choice. To be more specific, it investigates whether the provision of battery and vehicle leasing can increase the preference for battery electric vehicle. It is found that the attractiveness of BEV is significantly increased when battery leasing is offered on top of buying; however, when vehicle leasing is also provided for all car types, this effect vanishes for BEV and the preference for PHEV even slightly decreases. In both cases the aggregate impacts are rather small.

The rather insignificant aggregate impact does not necessarily entail that people remain inert, because the impact on preference is expected to be heterogeneous among the population and dependent on each individual's initial preference when purchase is the only available business model. In order to reveal the impact of business models on different groups, we applied latent transition analysis on our choice data. The results indicate that around 6% of the population became more likely to choose EV while another 6% switched their choices in an opposite direction. These two flows likely cancelled each other out and led to a rather infinitesimal aggregate impact. In general, people who seriously tradeoff between CV and BEV are more likely to be affected by business models and change their preferences. The probability of switching not only depends on one's initial preferences for EVs but also individual-specific variables, including price level of intended car, knowledge of EV and various attitudes towards leasing.

Study 4: the impact of carsharing system characteristics on its potential to replace private car trips and reduce car ownership (Chapter 5)

This study looks at another business model namely carsharing. Since consumers do not have to worry about the uncertainties surrounding battery degradation and residual value, carsharing can provide easy access to EV for those who have doubts for owning EV, which may help to realize the potential of EV in reducing emission to a fuller extent. However, it is unclear whether the resistance for EV would compromise the potential of carsharing in replacing private car trips and reducing car ownership.

This study found that in general the fuel type of shared cars does not make any difference in the decision of reducing car ownership; as for the decision of replacing private car trips, BEVs are even preferred to CVs by some categories of consumers. Regarding other system attributes such as costs and availability, if the current performance level is already acceptable (within the range of our experiment), an improvement of the system performance in these aspects do not seem to have a significant impact on facilitating carsharing to replace car ownership or private car trips.

As for the relation between the decision of trip replacement and reducing car ownership, the possibility of giving up car ownership does not monotonously increase with the intention to replace private car trips, since our analysis show that people who intend to use carsharing to replace more trips are not necessarily more willing to give up their car.

Contribution of the thesis

The thesis makes the following methodological and practical contributions:

Methodological

The thesis illustrated how latent transition analysis can be applied in studying induced behavioral change and analyzing data from stated choice experiment. Latent transition analysis is usually applied for panel datasets collected over different timepoints, while our dataset comprises choice responses for a cross-sectional choice experiment which has multiple waves of choice data for the same choice tasks under different contexts (provision of business models). Compared to discrete choice models, latent transition analysis extracts in-depth insights regarding behavioral change: it is able to unravel different directions of changes and can also relate the pattern of change with initial preferences. This has practical relevance since it provides a new way of identifying target groups which are most susceptible for a certain policy/strategy, thereby facilitating tailored implementation of policies which can increase efficiency and reduce side effects. Latent transition models can serve the purpose of investigating the behavioral change induced by a wide range of intervention instruments including business strategies and government policies, especially when the induced behavioral change is heterogeneous among the population or even is in opposite directions for different people.

Practical

The first and foremost practical contribution of our thesis is establishing the significance of business models in EV adoption. We demonstrated that consumers prefer vehicle leasing to purchasing in case of BEV, and that at least some people have a higher tendency to purchase EV when the option of leasing is provided (albeit the aggregate impact of leasing on EV market share in our setting is not significant). Therefore, all stakeholders including governments and car manufacturers shall take these alternative business models into account when making EV-related policies/strategies.

The second practical contribution relates to the finding regarding the impact of deploying electric vehicles in the carsharing fleet. As mentioned earlier, the deployment of EVs further enhances emission/pollution reduction and increases EV acceptance (Schlüter & Weyer, 2019) which likely entails higher future sales; however, the resistance for EV may compromise the penetration of carsharing itself. Since I found that deploying electric vehicles has no negative or even slightly positive impact on the potential of carsharing in replacing private car trips and reducing car ownership, implementing incentives for EV deployment in carsharing fleets is expected to have positive synergy effects.

The final practical contribution is related to consumer preference heterogeneity. Since consumer preferences and behavioral change are found to be heterogeneous in almost all cases (fuel type, business model and carsharing), policies and strategies will achieve higher efficiency if they can identify the target group which is most susceptible to these policies/strategies. For example, introducing leasing to those who would seriously trade-off between BEV and CV may push them towards choosing BEV, while it is unlikely to have the same effect for someone who considers PHEV. Our analyses provide insights regarding the various variables which can be used in classification or identifying target consumers: apart from the common socio-demographics, attitude and initial preference (when only buying is available) for car types can also have an influence. In marketing terms, these correspond to “psychographic” and “behavioral” segmentation in contrast to the traditional demographic segmentation: attitudes imply the motivation behind choices which can help to shape the focus of promotion messages (e.g. stress convenience and compatibility with BEV in case of leasing); the online searching behavior and the information gathering behavior at the dealers can also be used as variables for segmentation (if consumers demonstrated no interest in EVs whatsoever, then there is little point in recommending leasing to reduce EV adoption barriers). \

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Samenvatting

Achtergrond

Wegverkeer is sterk afhankelijk van fossiele brandstoffen en is daardoor verantwoordelijk voor een reeks problemen zoals milieuvervuiling, broeikasgassen en afhankelijkheid van fossiele brandstoffen. Het op grote schaal vervangen van auto's die op fossiele brandstoffen rijden door elektrische auto's (EV's33), wordt gezien als een mogelijke, of zelfs noodzakelijke oplossing om dit probleem te verminderen. Veel nationale overheden hebben daarom voor 2030/2040, een verbod aangekondigd op de verkoop van nieuwe auto's die op fossiele brandstoffen rijden. Om dit doel te bereiken, hebben de overheden een aantal stimulerende regelingen opgesteld om de acceptatie van elektrische auto's te bevorderen. Desondanks is het marktaandeel van de elektrische auto's in de meeste landen vooralsnog klein.

Om auto's die op fossiele brandstoffen rijden daadwerkelijk uit te kunnen faseren, is het van cruciaal belang om zowel de consumentenvoorkeuren ten aanzien van de acceptatie van elektrische auto’s, als de belangrijkste obstakels voor grootschalige acceptatie in kaart te brengen. Deze inzichten kunnen overheden helpen in het ontwikkelen van effectievere beleidsmaatregelen. Er zijn verschillende redenen waarom het marktaandeel van elektrische auto’s nog klein is. De belangrijkste zijn de beperkingen in batterijtechnologie (hoge kostprijzen, beperkte reikwijdte, lange oplaadtijd, onzekerheid over de levensduur en de restwaarde), en het ontbreken van een goed ontwikkelde infrastructuur wat betreft oplaadmogelijkheden. Aangezien de meeste problemen betrekking hebben op batterijtechnologie, is financiering van onderzoek hiernaar, van essentieel belang om de elektrische auto op langere termijn aantrekkelijker te maken voor eindgebruikers. Wat vaak vergeten wordt, is dat de maatschappelijke waarde van de technologie zelf, geen vast gegeven

[33] Electrische auto's (EV's) kunnen worden onderverdeeld in plug-in hybrides (PHEV's) die aangedreven worden door zowel een batterij als een motor, en auto's die volledig op batterijen rijden (BEV's). Auto's die (conventioneel) op fossiele brandstoffen rijden, worden afgekort tot CV's

is. We kunnen daarom trachten de waarde van deze technologie te vergroten en daarmee drempels voor acceptatie ervan te verminderen.

Het belang van businessmodellen

De waarde van technologie is afhankelijk van hoe die in de markt wordt gezet. Dit wordt wel het 'businessmodel' genoemd. De twee basiselementen van businessmodellen die van belang zijn voor consumenten, zijn de waarde van het eigenlijke product of de dienst zoals het wordt aangeboden door een bedrijf, en het verdienmodel, de manier hoe een bedrijf zijn kosten in rekening brengt bij zijn klanten (Bohnsack et al. 2014; Kley et al. 2011). Bijvoorbeeld, bij het meest gebruikte businessmodel in de autobranche, heeft de auto waarde voor de eigenaar, en is het verdienmodel het direct betalen van de aanschafprijs.

Omdat de batterijtechnologie op dit moment nog een belemmering vormt om elektrische auto's breed in de markt te zetten, zijn de huidige businessmodellen mogelijk niet toereikend. Als we dezelfde technologie met behulp van andere businessmodellen in de markt zetten, kan dat leiden tot andere economische uitkomsten (Chesbrough 2010). In het geval van elektrische auto's, kun je zowel door leasen als door het delen van een auto (autodelen) de hoge financiële kosten van de aanschaf van een auto als consument vermijden. Ook worden risico's verlegd van de consument naar de exploitant, zoals bijvoorbeeld dat batterijtechnologie wordt achterhaald of onverwachte waardedaling bij verkoop op de tweedehands markt.

Alternatieve businessmodellen kunnen dus bijdragen aan het vergroten van de marktpenetratie van elektrische auto's. Deze kunnen zelfs noodzakelijk zijn om elektrische auto's commercieel rendabel te laten zijn. In de Verenigde Staten worden op dit moment bijna 80% van de BEV's geleast, in plaats van gekocht en het totale wagenpark van de VS bestaat voor 30% uit leaseauto's[34]. Dit impliceert dat het aandeel consumenten dat een elektrische auto least, veel hoger is dan het aandeel dat een conventionele auto least. Om te onderzoeken wat de mogelijkheden zijn van businessmodellen om de acceptatie van elektrische auto's te vergroten, moeten we empirisch onderzoek verrichten.

Kennisleemte

Er is al zeer veel onderzoek verricht binnen de transportsector naar consumentenvoorkeuren voor elektrische auto's. De meeste onderzoeken zijn gedaan met de stated preference methode en zijn gefocust op de eigenschappen van de auto en de bijbehorende oplaadinfrastructuur. Een andere onderzoekslijn kijkt voornamelijk naar welke invloed psychologische factoren hebben op de voorkeuren voor elektrische auto's. Vreemd genoeg benoemen de meeste onderzoeken niet van welk businessmodel wordt uitgegaan35. Dit maakt het onmogelijk om de invloed van het businessmodel op basis van reeds uitgevoerd onderzoek vast te stellen.

Anderzijds zijn er verschillende onderzoeken vanuit het bedrijfsleven, die de invloed van businessmodellen combineren met duurzame technologieën, waaronder elektrische auto's (Kley et al. 2011; Budde Christensen et al. 2012; Wells 2013; Bohnsack et al. 2014). Hoewel al deze studies in essentie onderzoekend zijn, gaan ze uit van een conceptueel kader, bediscussiëren ze theorieën over de mogelijke invloed van businessmodellen, of voeren case studies uit. Voor zover ik heb kunnen vaststellen zijn er nog geen kwantitatieve empirische onderzoeken geweest die ons inzicht kunnen geven in de patronen en de mate van invloed van verschillende businessmodellen op de acceptatie van elektrische auto's.

Onderzoeksdoel

Tot op heden is er nog geen empirische studie uitgevoerd die door middel van kwantitatief onderzoek de consumentenvoorkeuren voor verschillende businessmodellen meet, en hoe deze de acceptatie van elektrische auto's beïnvloedt. Het hoofddoel van deze thesis is om inzicht te

[34] https://www.bloomberg.com/news/articles/2018-01-03/why-most-electric-cars-are-leased-not-owned

[35] See (Valeri & Danielis 2015; Glerum et al. 2014) for two exceptions.

verkrijgen in consumentenvoorkeuren voor verschillende businessmodellen in de context van elektrische auto's. Tevens onderzoek ik de invloed die het aanbieden van alternatieve businessmodellen kan hebben op het marktaandeel van elektrische auto's. De businessmodellen waar ik van uit ga zijn het leasen van de batterij, het leasen van de auto en het delen van de auto.

Zoals ik al eerder schreef, willen veel landen de auto's die op fossiele brandstoffen rijden uitfaseren. Om dit doel te bereiken, zijn er effectieve en efficiënte stimulansen nodig om de belemmeringen weg te nemen die de elektrische auto op de markt ondervindt. Dit onderzoek kan inzichten verkrijgen die als input kunnen dienen bij het nemen van beslissingen omtrent het beleid om de elektrische auto te stimuleren. Derhalve heeft dit onderzoek een grote maatschappelijke relevantie.

Opbouw van de thesis

De thesis begint met een literatuurstudie van onderzoeken die zijn verricht naar consumentenvoorkeuren ten aanzien van elektrische auto's. Dit doe ik om een overzicht te creëren van reeds bestaande bevindingen die bijdragen aan onderzoeken over de acceptatie van elektrische auto's in het algemeen. Ik heb twee empirische onderzoeken gewijd aan het businessmodel leasen van de batterij en leasen van de auto. In het derde hoofdstuk onderzoek ik de keuze van het businessmodel gecombineerd met de keuze voor het type brandstof van de auto. Dit geeft inzicht in de voorkeuren van de consument voor deze twee businessmodellen. Maar zelfs als leasen het meest gewaardeerd wordt voor BEV's, wil dat nog niet zeggen dat een groter aanbod van lease mogelijkheden van elektrische auto's zal leiden tot meer verkoop van deze auto's. De resultaten van deze studie maken duidelijk dat degenen die leasen prefereren, tóch de keuze zouden maken voor een BEV, ook als kopen de enige mogelijkheid zou zijn. In hoofdstuk vier onderzoek ik hoe de beschikbaarheid van alternatieve businessmodellen de keuze voor het brandstoftype, en hiermee het marktaandeel van elektrische auto's beïnvloedt. Hoofdstuk vijf behandelt het businessmodel van het delen van een auto. Hierin onderzoek ik of het inzetten van elektrische deelauto's de keuze om een auto te delen of aan te schaffen kan beïnvloeden. De bevindingen van deze onderzoeken vat ik hieronder samen.

Theorie en methoden

Alle toegepaste modellen die het keuzegedrag beschrijven in de empirische studies, zijn gebaseerd op RUM (Random Utility Maximization) theorie. Deze theorie stelt dat individuen altijd de keuze maken voor het alternatief dat hen het meeste nut oplevert. Het nut van een alternatief is de som van twee componenten, een systematisch nut dat gebaseerd op de kenmerken van het alternatief en de gewichten die ze daaraan geven, en een willekeurige 'fout' welke onbekend is voor de onderzoeker. RUM theorie is de meest gebruikte theorie bij het modelleren van reisgedrag. Meer details zijn te vinden in het boek van Train (2003).

Voor de specifieke modellen heb ik voornamelijk geavanceerde discrete keuze modellen toegepast, waaronder mixed logit- en hybrid choice models. Tevens heb ik latente transitie analyse gebruikt bij het bestuderen van gedragsverandering. Alle modelschattingen zijn gebaseerd op dezelfde dataset die verzameld is in juni 2016 via een enquête onder alle auto bezitters en potentiele autobezitters in Nederland. De uiteindelijke steekproef bestond uit 1003 respondenten.

Bevindingen

Studie 1: Literatuurstudie van onderzoeken naar consumentenvoorkeuren ten aanzien van elektrische auto's (hoofdstuk 2).

In dit hoofdstuk heb ik een literatuurstudie uitgevoerd naar reeds uitgevoerd onderzoek naar consumentenvoorkeuren ten aanzien van elektrische auto's. Dit heb ik gedaan om een zo volledig mogelijk beeld te krijgen van wat er momenteel bekend is op dit gebied en om te ontdekken wat er nog ontbreekt. De grote meerderheid van de studies naar individuele voorkeuren ten aanzien van elektrische auto's gebruiken de economische benadering. Dit doen zij omdat met deze benadering de invloed van zowel de kenmerken van de auto als de individuele eigenschappen die de voorkeuren ten aanzien van elektrische auto's beïnvloeden onderzocht kunnen worden. Ik heb een opsomming gemaakt van een reeks kenmerken die belangrijk blijken te zijn voor de keuze van een type auto. Hieronder vallen financiële en technische kenmerken zoals aanschafprijs, brandstofprijs, het bereik in kilometers en de prestaties van de auto. In het geval van elektrische auto's zijn ook de oplaadinfrastructuur en de overheidsstimulansen cruciaal. De voorkeuren voor deze kenmerken en elektrische auto's in het algemeen, zijn over het algeheel niet eenduidig. De verschillen kunnen voor een deel verklaard worden door individu-specifieke eigenschappen. Bijvoorbeeld: sociaaleconomische en demografische, psychologische, ruimtelijke, mobiliteits- en auto gerelateerde factoren, ervaring met elektrische auto's en sociale invloeden. Ik heb meerdere onderzoekleemtes gevonden, waarvan de meest relevante voor mijn volgende studies is, dat eerdere onderzoeken zich niet richten op de mogelijke rol van businessmodellen bij het stimuleren van de acceptatie van elektrische auto's.

Studie 2: Consumentenvoorkeuren voor innovatieve businessmodellen in de context van acceptatie van elektrische auto's (hoofdstuk 3).

Deze studie onderzoekt de consumentenvoorkeuren voor innovatieve businessmodellen in de context van acceptatie van elektrische auto's. Ik focus hierbij op de businessmodellen ‘het leasen van de batterij’ en ‘het leasen van de auto’. In dit onderzoek wordt de keuze van het businessmodel gezien als een extra optie die je kunt kiezen, gecombineerd met de keuze voor het type brandstof waarop de auto rijdt. Omdat leasen sommige tekortkomingen van bepaalde technologieën, zoals BEV (denk bijvoorbeeld aan een hogere aanschafprijs), vermindert, kan de mate van voorkeur om te leasen verschillen, hetgeen afhankelijk is van de keuze van het brandstoftype. Verder heb ik de relatie onderzocht tussen de houding van mensen ten aanzien van leasen, en hun voorkeur voor leasen.

De studie toont aan dat wanneer alle drie de businessmodellen beschikbaar zijn (aanschaf, autolease en batterij lease), het leasen van een auto de meest populaire optie is voor BEV's. Het leasen van de batterij is de minst populaire optie. Dit betekent dat autolease een toegevoegde waarde is voor BEV's, en dat het leasen van de batterij slechts voor een kleine groep aantrekkelijk is. Echter, in het geval van (plug-in) hybride auto's en auto's die op fossiele brandstoffen rijden, heeft aanschaffen de voorkeur boven leasen. Dit impliceert dat de voorkeur voor een businessmodel afhankelijk is van het brandstoftype, zoals werd verwacht. Onze resultaten suggereren ook dat attitudes een belangrijke invloed hebben op de voorkeuren voor businessmodellen. Zo leidt een hogere waardering voor het gemak van leasen, tot een grotere kans om te kiezen voor autolease, waarbij het niet uitmaakt of dit een elektrische auto is of een auto die rijdt op fossiele brandstoffen. Anderzijds zullen mensen die autobezit op prijs stellen, minder snel kiezen voor het leasen van een auto. Tot slot zullen zij die geloven dat elektrische auto's meer geschikt zijn om te leasen dan traditionele auto's, meer geneigd zijn een BEV te accepteren door middel van batterij lease of autolease. Voor de kans op het leasen van een PHEV is dit geen belangrijke factor.

Studie 3: De invloed van businessmodellen op de acceptatie van elektrische auto's: een latente transitie analyse benadering (hoofdstuk 4).

Dit onderzoek neemt een andere invalshoek dan de tweede studie. In plaats van te focussen op de keuze van businessmodellen, kijkt de derde studie naar de keuze van het brandstoftype. Het doel hierbij is om te ontdekken hoe de beschikbaarheid van businessmodellen deze keuze beïnvloedt. In het bijzonder wordt onderzocht of het aanbieden van batterij- en autolease de voorkeur voor een BEV kan vergroten. Ik heb ontdekt dat de aantrekkelijkheid van BEV's sterk toeneemt wanneer bij aankoop van een auto de batterij op leasebasis wordt aangeboden. Maar als ook autolease wordt aangeboden voor zowel BEV's, PHEV's als auto's die op fossiele brandstoffen rijden, verdwijnt dit effect voor BEV's. Voor PHEV's daalt de voorkeur zelfs licht. In beide gevallen is het geaggregeerde totale effect tamelijk klein.

Dat dit geaggregeerde totale effect niet zo groot is, betekent niet noodzakelijkerwijs dat mensen hun keuzes niet veranderen. De verwachting is dat mensen sowieso verschillende voorkeuren hebben en dat die voorkeuren afhankelijk zijn van ieders initiële voorkeur in de situatie wanneer aankoop het enige beschikbare businessmodel is. Om de invloed van businessmodellen op verschillende groepen van individuen te laten zien, heb ik latente transitie analyse toegepast. De resultaten laten zien dat rond de 6% van de bevolking eerder een elektrische auto zou kiezen als beide typen leasen wordt ingevoerd, terwijl een andere 6% hun keuze wijzigde in de tegenovergestelde richting. Deze twee bewegingen hebben elkaar waarschijnlijk opgeheven en leidden daardoor tot een verwaarloosbaar klein geaggregeerd effect. Over het algemeen zullen mensen die bij het kopen van een auto zowel kijken naar auto's die op fossiele brandstoffen rijden als naar BEV's, meer beïnvloed worden door businessmodellen en hierdoor hun voorkeuren wijzigen als leasen wordt ingevoerd. De kans dat ze van voorkeur wisselen hangt niet alleen af van iemands aanvankelijke voorkeur voor elektrische auto's, maar ook van persoonlijke variabelen, waaronder de prijs van de beoogde te kopen auto, de kennis van elektrische auto's en verschillende houdingen ten opzichte van leasen.

Studie 4: De invloed van eigenschappen van autodeelsystemen op de potentie om privé autoritten te vervangen en autobezit te verminderen (hoofdstuk 5).

Deze studie kijkt naar het businessmodel autodelen. Consumenten hoeven zich bij autodelen geen zorgen te maken over onzekerheden wat betreft de kwaliteitsvermindering van de batterij (lagere actieradius) en de restwaarde van de auto. Hierdoor kan het autodelen een makkelijke opstap zijn naar een elektrische auto voor degenen die twijfels hebben om er zelf een aan te schaffen. Dit kan vervolgens helpen om op grotere schaal vermindering van uitstoot te realiseren. Het is echter onzeker of de weerstand tegen elektrische auto's de potentie dat autodelen privé autoritten vervangt en autobezit vermindert in gevaar brengt.

In dit onderzoek is gebleken dat het type brandstof van deelauto's over het algemeen geen verschil maakt in de beslissing om wel of niet een auto te kopen. Maar bij de keuze om privé autoritten te vervangen door deelauto's, verkiezen bepaalde categorieën consumenten BEV's boven auto's die op fossiele brandstoffen rijden. Als je kijkt naar andere eigenschappen van autodeel systemen, zoals kosten en beschikbaarheid (indien het huidige aanbodniveau voldoende acceptabel is, voor zover ons experiment dit kan inschatten), lijkt het verbeteren hiervan geen significant effect te hebben op het stimuleren van autodelen met als doel autobezit of privé autoritten te vervangen.

Met betrekking tot verband tussen het gebruik maken van autodelen en het reduceren van autobezit laat onze analyse zien dat mensen die zeggen meer gebruik te gaan maken van autodelen voor ritten waarvoor ze nu hun eigen auto gebruiken, niet noodzakelijkerwijs meer geneigd zijn om hun eigen auto op te geven.

Bijdrage van de thesis

Deze thesis levert de volgende methodologische en praktische bijdragen op.

<u>Methodologie</u>

Mijn thesis laat zien hoe latente transitie analyse toegepast kan worden in het bestuderen van gedragsverandering en data analyse van stated choice experimenten. Latente transitie analyse wordt meestal gebruikt voor data die zijn verzameld voor dezelfde mensen op verschillende momenten in de tijd. Onze dataset bevat keuzeantwoorden die zijn verzameld met een cross-sectioneel keuze-experiment. In dit experiment wordt respondenten gevraagd om eerst een keuze te maken tussen CV, BEV en PHEV alternatieven die zijn gebaseerd op de huidige businessmodellen. In enkele vervolgvragen, die kunnen worden gezien als verschillende waves, wordt respondenten gevraagd of ze hun keuze aanpassen als nieuwe alternatieven worden geïntroduceerd die zijn gebaseerd op alternatieve businessmodellen. Het toepassen van latente transitie analyse op deze data geeft meer diepte-inzichten in gedragsverandering vergeleken met standaard discrete keuzemodellen. Het is daarmee mogelijk om verschillende richtingen van veranderingen te ontrafelen en je kunt ook het patroon van verandering verbinden met de initiële voorkeuren. Dit heeft een praktisch nut, omdat het een nieuwe manier biedt om doelgroepen te identificeren die het meest gevoelig zijn voor een bepaald beleid of strategie. Hierdoor kunnen op maat gesneden beleidsmaatregelen worden ontwikkelt, wat de efficiëntie vergroot en de bijwerkingen verkleint. Latente transitie modellen kunnen als doel hebben om de gedragsverandering die teweeggebracht wordt door een grote hoeveelheid interventie-instrumenten te onderzoeken, waaronder business-strategieën en overheidsbeleid. In het bijzonder geldt dit als de teweeggebrachte gedragsverandering niet eenduidig is onder de bevolking of zelfs voor verschillende mensen in tegenovergestelde richtingen verloopt.

Praktijk

De eerste en meest praktische bijdrage van deze thesis is het constateren van het belang van businessmodellen bij de acceptatie van elektrische auto's. We hebben laten zien dat consumenten het leasen van een BEV prefereren boven het kopen hiervan. Ook zijn er enkele mensen die een grotere neiging hebben om een elektrische auto te kopen wanneer de optie van leasen wordt aangeboden (alhoewel het totale effect van leasen op het marktaandeel elektrische auto's in onze setting niet substantieel is). Daarom zullen alle belanghebbenden, inclusief overheden en autofabrikanten, rekening moeten houden met deze alternatieve businessmodellen bij het opstellen van beleid en strategieën die verband houden met elektrische auto's.

De tweede praktische bijdrage houdt verband met de bevinding van het belang om elektrische auto's in te zetten in het wagenpark van deelauto's. Zoals al eerder aangegeven, draagt het inzetten van elektrische auto's bij aan de vermindering van de schadelijke uitstoot en vergroot dit de acceptatie van elektrische auto's (Schlüter & Weyer, 2019). Dit laatste kan in de toekomst tot een grotere verkoop leiden. Daarentegen kan de weerstand tegen elektrische voertuigen mogelijk de opmars van het autodelen belemmeren.

Ik heb geconstateerd dat het inzetten van elektrische auto's geen negatief maar zelfs een positief effect heeft op de potentie van autodelen om privé autoritten te vervangen en het autobezit te verminderen. Daarom is te verwachten dat het inzetten van stimulansen om elektrische auto's op te nemen in het autopark van deelauto's, een meerwaarde zal hebben ten opzichte van het alleen aanbieden van elektrische auto's zonder het businessmodel autodelen, of het alleen aanbieden van autodelen zonder elektrische auto's.

De laatste praktische bijdrage hangt samen met de heterogeniteit van consumentenvoorkeuren. Omdat consumentenvoorkeuren en gedragsverandering in bijna alle casussen (brandstoftype, businessmodel en autodelen) niet eenduidig zijn, zullen beleid en strategieën effectiever zijn als zij de doelgroep kunnen identificeren die hiervoor het meest bevattelijk is. Als je bijvoorbeeld leasen aanbiedt aan iemand die serieus de opties BEV of CV aan het afwegen is, kan dit het zetje geven om voor BEV te kiezen. Het is onwaarschijnlijk dat dit bij iemand die een PHEV overweegt, hetzelfde effect heeft. Onze analyse geeft inzicht in de verschillende variabelen die gebruikt kunnen worden bij het indelen of identificeren van consumenten doelgroepen. Los van de gebruikelijke sociaal demografische factoren, kunnen houding en aanvankelijke voorkeur voor een brandstoftype (wanneer alleen aanschaf een optie is) van invloed zijn. In marketing termen sluit dit aan bij psychografische- en gedragssegmentatie, dit in tegenstelling tot de traditionele demografische indeling: houdingen wijzen naar de motivatie achter de keuzes, en kunnen helpen om de focus van de stimuleringsboodschappen vorm te geven (bijvoorbeeld benadrukken van gemak en compatibiliteit met BEV bij leasen). Het online zoekgedrag en het informatie verzamelen bij de dealers kan ook gebruikt worden als variabelen bij de segmentatie (als consumenten geen enkele interesse tonen in elektrische auto's, dan heeft het weinig zin om leasen aan te bevelen, om bij hen de drempels voor acceptatie van automatische auto's te verminderen).

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