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The impact of business models on electric vehicle adoption: A latent transition analysis approach

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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.

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

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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 3–4 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.

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.

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. Fig. 1 illustrates this conceptualization.

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:

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

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

The two utility functions adopt exactly the same specification and the superscript denotes the corresponding choice. U_{nit} denotes

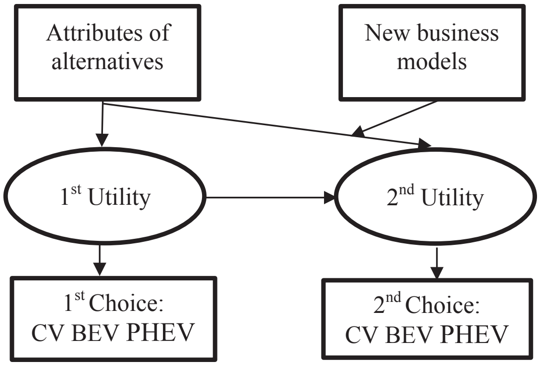

Fig. 1. Conceptual model 1: average impact of business models.

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$\sigma^1_{\epsilon_i}$. ε_{nit} is an unobserved error term that is assumed to follow an extreme value distribution.

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

$$\boldsymbol{\beta_i^2} = \boldsymbol{\eta_i \beta_i^1}$$

$$\beta^2_{i0} = \eta_{i0}\beta^1_{i0}$$

$$\epsilon^2_{ni} = \eta_{i\epsilon}\ \epsilon^2_{ni}$$

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:

$$L = \int_{\epsilon} \prod_{t\in T}\prod_{i\in j} P^1_{nit}\left(y^1_{nit}=1|\boldsymbol{X_{it}};\ \boldsymbol{\beta}^1,\ \beta^1_{i0}\sigma^1_{\epsilon_i}\right)^{y^1_{nit}} P^2_{nit}\left(y^2_{nit}=1|\boldsymbol{X_{it}};\ \boldsymbol{\beta}^2,\ \beta^2_{i0}\sigma^2_{\epsilon_i}\right)^{y^2_{nit}} \frac{1}{\sigma^1_{\epsilon_i}}\Phi\left(\frac{\epsilon^1_{ni}}{\sigma^1_{\epsilon_i}}\right) d\,\epsilon_{nj}$$

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.

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. Fig. 2

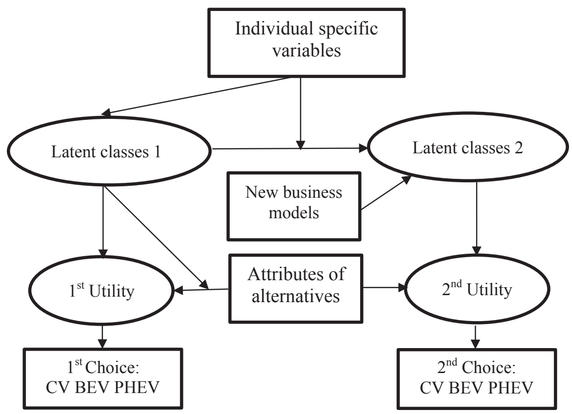

Fig. 2. Conceptual model 2: heterogeneous impact of business models.

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.

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).

3. Data collection

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

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
		> 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

* Those who received higher vocational or university education.

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

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.

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.

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.

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.

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. Fig. 3 shows an example of a choice task.

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/100 km)	2	4	6
	PHEV (euro/100 km)	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

[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

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

4. Results

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

Table 4
Estimation result of business model impact model.

Name			Only battery leasing available			All leasing available		
			Value	Std. error	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/100 km)			−0.215	0.0239	−9.01	−0.212	0.0226	−9.39
Driving range (100 km)			0.131	0.0482	2.72	0.117	0.0478	2.45
All-electric range (100 km)			0.500	0.159	3.14	0.619	0.147	4.20
Fast charging availability (per 100 km)			−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.

(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 parametersη_i, η_{i0} and$\eta_{i\epsilon}$. However, none of the attribute shift parameters η_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 $\eta_i$to1 and re-estimated the model.

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 (10–30 min) while many studies use a wide range including both fast and slow charging (for example 10 min–8 h). 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.

Table 5
Model fit of the latent class choice models.

	Number of classes	LL	BIC	Npar	R(0)	R
Choice in wave 1	1	−5172	10,419	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	10,198	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

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.

4.2.1. 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 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 7 presents the class membership model in the case of the 1st choice. In general, few individual variables have a significant

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

Table 7
Class membership model of first choice.

	1 CV buyers (Ref is PHEV)	2 CV + BEV (Ref is PHEV)	3 Serious interest in EV (Ref is PHEV)	4 EV buyers (Ref is PHEV)
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 $p < 0.10$.

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.

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)[1] 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 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.

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

[1] 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.

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

Wave 1 class membership	Parameters	Wave 2 class membership			
		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

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

Table 10
WTP estimates of each class and relative differences.

Attributes	CV	CV + BEV	Serious Interest EV	EV	Relative differences from CV Class	CV + BEV	Serious Interest EV	EV
BEV						1154	−1002	9936
PHEV						−14,448	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: The unit of currency is euro (€).
The values are calculated for the case when the current/stated car costs €15000.
In the calculation of relative changes, the values of statistically non-significant coefficients are fixed to 0.
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.
* The corresponding taste parameters are non-significant at $p < 0.10$.

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.

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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