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Influence of Social Networks on Latent Choice of Electric Cars: A Mixed Logit Specification Using Experimental Design Data

Soora Rasouli · Harry Timmermans

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Abstract Electric cars can potentially make a substantial contribution to the reduction of pollution and noise. The size of this contribution depends on the acceptance of this new technology in the market. This paper reports on the design and results of an elaborate stated choice experiment to investigate the effects of vehicle attributes, contextual and social network attributes on the latent demand for electric cars. The study contributes to the existing literature primarily by explicitly modelling the effects of different elements of social networks on the latent demand for electric cars. Moreover, the number of attributes included in the study design exceeds the typical number of attributes used in previous research, making the model more sensitive to a larger spectrum of variables. Two different mixed logit models are estimated: one with random parameters for vehicle attributes and contextual attributes and fixed effects for the social network attributes; one with random effects for social network attributes and fixed effects for the remaining attributes. Results indicate substantive differences between these two models in terms of the shape of utility curves. Overall, vehicle attributes are most important in the choice of electric cars, followed by social influence attributes. The effects of social network are relatively small.

Keywords Electric cars · Mixed logit model · Social network

1 Introduction

Transport significantly contributes to environmental problems such as pollution and noise. Urban planners and transportation engineers have attempted to reduce the contribution of transport to these environmental problems by designing resilient

S. Rasouli · H. Timmermans (✉)
Department of Urban Science and Systems, Urban Planning Group, Eindhoven University of Technology, PO Box 513, Vertigo 8.25, 5600MB Eindhoven, The Netherlands
e-mail: h.j.p.timmermans@tue.nl

S. Rasouli
e-mail: s.rasouli@tue.nl

urban and transportation systems. For example, the New Urbanism Movement has advocated that high-density, mixed-use urban environments induce people to use slow modes of transport, implying a reduction in pollution and noise levels.

The transportation literature has accumulated a corresponding overwhelming body of empirical knowledge about the relationship between properties of the built environment and travel behaviour (e.g. Ewing and Cervero 2010). Although the results of these studies are mixed, the dominant findings seem to indicate that the strength of the relationship between high-density, mixed-use environments and the use of slow modes of transport is relatively weak. Similarly, the success of high density, mixed-use urban environments in reducing overall mobility levels is modest at best.

Several considerations may explain these findings. First, the assumed relationship between density and mobility is, ceteris paribus, almost tautological. If individuals can find the locations for their activities at closer distance, as high density would imply, by definition their mobility in terms of distance travelled should be less. Thus, any statistical relationship between density and travel behaviour does not necessarily reflect people's preferences and true underlying behaviour. Second, common reasoning ignores the fact that activity locations at close range do not stimulate individuals to behave in efficient ways. Consequently, high density often co-varies with higher travel frequency, which in turn, at least partially, counterbalances the positive effects of closer distance. Thirdly, daily travel is not a need in its own right. Rather, as has been commonly accepted in activity-based analysis (e.g. Timmermans et al. 2002), individuals travel to participate in activities, which in turn are conducted to satisfy needs and desires (e.g. Miller 2005). Individuals have several commitments reflecting a set of life trajectories decisions and pursue different careers such as a housing career, a job career, etc. The utility individuals derive from their long-term life trajectories careers tend to be substantially higher than the disutility of travel. Thus, in organizing their daily lives, most individuals tend to give priority to their job and housing careers and simply take the resulting travel for granted, as long as particular constraints are not violated. This principle has become even more prevalent as the result of an increasing share of women participating in the workforce and the rise of dual-earner households. In many cases, it is a coincidence that spouses can both find a job very close to their home, especially if the jobs are relatively scarce. Under such circumstances, at least one of the spouses may need to travel longer distance. Finally, the general increase of accumulated wealth has implied that fewer constraints act on individual mobility. A large share of the population of Western societies can afford buying a second car and thus will do so, also considering the convenience and flexibility the car brings in organizing daily activities, in particular when faced with full agendas and time pressure.

If we move the focus of attention from developed Western countries to emerging societies with high economic growth such as China and India, it has become clear that increased social status and the growth of disposable income that comes with it, are reflected in consumption patterns, similar to those observed in developed countries before. Despite the fact that environmental concerns may even be more severe in such countries and that certainly the general awareness is, increased income and status are manifested in one or more cars. The problem here is that we cannot deny individuals in these countries to act in any other way. It implies that despite national and international urban, transportation and environmental policies, mobility will rapidly increase globally, further enhancing existing environmental problems. These observations do not imply that these policies should be abandoned; it merely means that expectations should not be high.

The limited contribution of urban and transportation policies in reducing environmental problems also implies that a true solution should come from technology. In that regard, significant progress has been made recently in developing alternative fuel cars, such as electric and hybrid cars. This new technology based on non-fossil fuels not only means a smaller contribution to the depletion of scarce resources, but also less emission and energy consumption. The question, however, is whether the market will accept this new technology. Popular media and early industry reports seem to suggest that the market share for such new technology is still limited (e.g., Karfisi et al. 1978; Morton et al. 1978; Beggs and Cardell 1980). Concerns have been raised about the general performance of electric cars, relative to conventional cars, and their battery life and recharging limitations. Moreover, there may be issues with regard to the image projected by this type of car. This scepticism is not uncommon to technological innovations and diffusion processes in general. In the beginning, after the introduction of new technology, individuals are often reluctant to accept and buy the technology. Only after a certain threshold has been reached, general acceptance tends to increase rapidly, to slow down again until some saturation point has been reached.

In light of this introduction, the aims and objectives of this study are two-fold. First, the aim is to better understand the latent choice of electric cars as a function of (i) their attributes, (ii) context, (iii) the nature of reviews it receives, (iv) the acceptance of the electric car by members of various elements of social networks (relatives, friends, co-workers and peers), and (v) socio-demographic variables. This study is designed to examine the relative importance of these factors in the decision whether or not to buy an electric car as the primary vehicle of the household. In particular, a stated choice experiment is designed to better understand this decision process and derive the relative importance of these factors in the choice of an electric car, with a special focus on social influence. Considering the objective of studying the impact of social influences, the design of the experiment differs from conventional stated preference and choice designs, which typically vary only the attributes of the choice alternatives. The second aim of this study therefore is to extend conventional choice experiments to allow the estimation of social influence on choice behavior.

To these ends, the article is structured as follows. First, we will discuss the existing but still limited literature on the acceptance and choice of electric cars. This section serves to put our research findings in a wider context. Next, we will discuss the design of the experiment, followed by a discussion of the sample and its characteristics. The following section is concerned with a discussion of the analyses and results. In particular, the dichotomous choice data will be analysed using a mixed logit model. The dependent variable is the latent choice, whereas attribute levels of the car, context, nature of reviews, various social influences, operationalized in terms of shares of people of that social network owning an electric car, and a set of socio-demographic variables serve as independent variables. In addition, as reflected in the choice of a mixed logit model, unobserved heterogeneity will be captured by estimating distributional effects of some key independent variables. The article will be completed by a set of conclusions and a discussion of policy implications.

2 Body of Knowledge

Although electric car technology has only recently matured, studies examining the latent demand for electric and hybrid cars have appeared in the literature since the late 1970s (e.g., Karfisi et al. 1978; Train 1980; Beggs and Cardell 1980). This seminal work focused on the estimation of the latent demand for alternative-fuel vehicles in general. It was the start of a constant flux of studies, which recently seems to have regained increased momentum as evidenced by multiple recent publications (e.g.; Mabit and Fosgerau 2011; Rasouli and Timmermans 2013; Glerum et al. 2011; Glerum and Bierlaire 2012; Achnicht 2012; Jensen et al. 2012).

Previous work on the latent demand for electric cars can be broadly divided into qualitative studies and stated choice experiments. Qualitative studies have used group interviews, games and similar less-structured research methods to better understand consumer response to the concept of the electric car, its image, consumer concerns, etc. In contrast, stated choice experiments have applied a more systematic approach to the problem by observing consumer response (intention to buy) to a set of profiles, representing different combinations of attribute levels that describe an electric car. Experimental design principles are applied to construct the set of attribute profiles that describe possible car designs in conjunction with price and cost conditions. These studies vary in terms of the number and kind of attributes included in the experiment, principles underlying the design of the experiment, and the choice model that is estimated.

Qualitative studies aim at better understanding in general terms consumer acceptance and concerns about vehicles with new fuel types and identifying the factors that affect preferences, concerns, willingness to pay and ultimately intention to buy. Many such studies have relied on focus groups, and were conducted by professional firms in non-academic settings for the car industry. However, a similar approach has also been followed in academic research. For example, Hinkeldein et al. (2011) used four focus groups to discuss four different concepts of integrated e-mobility services, one of which concerned 'battery leasing', allowing owners of an electric vehicle to use battery swap facilities all over Germany at a fixed price. Another concept, 'electricity at a fixed price', provides easy access to charging stations which offer green electricity only, while the concept 'public transport and e-mobility' offers green electricity for privately owned EVs as well as annual local public transport tickets. Consistent with early research (e.g. Christensen et al. 2010; Lidicker et al. 2010; Cocron et al. 2011), they found that high vehicle price, uncertainties regarding maintenance and resale value, size of batteries and limited operation ranges were main obstacles to the adoption of electric cars.

A second approach in these qualitative studies involves the use of gaming methods. It tends to differ from focus groups and similar methods in that a more structured approach is adopted. For example, Kurani et al. (1994, 1996) employed interactive stated lifestyle techniques, which systematically prompt subjects about their purchase decision-making and lifestyle plans. The method first constructs hypothetical choice situations from data about subjects' real activity-travel behavior. Next, interviews are conducted to explore the subject or household responses to the introduction of say an electric car. Kurani et al. (1994) investigated responses to minimum range, emergency, vehicle fleet optimization and comfortable range scenarios. Potential responses often cover a wider spectrum of options, including carpooling, renting, borrowing, rescheduling of activity-travel patterns, etc. For the purpose of this study, the results of these qualitative studies have been instrumental in selecting factors influencing the choice of electric car.

Table 1 provides an overview of stated choice experiments. It demonstrates that very few studies have looked at the potential demand for electric cars only, without considering other engine types; most studies have taken a broader perspective and examined the interest in alternative vehicles in general. For example, Brownstone et al. (1996) included gasoline, natural gas, methanol and electric vehicle types. Similarly, Ewing and Sarigöllü (1998) distinguished between several alternative fuel, gasoline and electric cars. In a major Canadian study (Horne et al. 2005), gasoline, propane, natural gas, diesel, methanol, ethanol, hybrid, hydrogen and electric were included, although in the choice experiment a distinction was made between gasoline, alternative fuel, hybrid-electric and hydrogen. Mabit and Fosgerau (2011) similarly included gasoline, hydrogen, hybrid, biodiesel and electric vehicles.

As shown in Table 1, some clear trends can be observed in the design and implementation of these experiments and the modelling of observed choices to predict the latent demand for electric cars and vehicles with alternative fuels. These trends tend to be in line with developments in the design of experiments and advances in discrete choice modelling at large. Brownstone and his co-workers (1996, 1999, 2000; Bunch et al. 1995) were among the first to conduct a comprehensive study on the latent demand for alternative fuel vehicle. Compared to most other efforts, their study was embedded in the larger problem of household vehicle holdings and transitions. They estimated a multinomial logit model (MNL) to predict the choice of vehicle as a function of a set of attributes. The multinomial logit model has remained the standard for a long time, only recently being replaced by the mixed logit (ML) and the hybrid choice model (HCM). Examples of the mixed logit model include Brownstone and Train (1999) and Mabit and Fosgerau (2011), while Glerum and Bierlaire (2012) and Jensen et al. (2012) applied the hybrid choice model. The most important reason for the mixed logit to become the new bar in applied discrete choice modelling in general is that it allows estimating the effects of unobserved heterogeneity which may particularly affect the choice problem at hand (for example, attitude about the environment, see Ikeda et al. 2000; Kishi and Satoh 2005; Johansson et al. 2006; Kahn 2006; Erdem et al. 2010). The hybrid choice model represents an attempt to account for such unobserved heterogeneity by explicitly measuring attitudes and representing these in the model (e.g., Walker and Ben-Akiva 2002; Ben-Akiva et al. 2002).

Stated choice models have adopted different experimental design principles to construct the profiles of alternative fuel cars and choice sets. In the early years, studies were based on orthogonal main-effects fractional factorial design to define the profiles. Since the mid 2000s, this approach seems to have been replaced by a pivoted design, using the current car as the pivot. This means that all profiles become personalised. This operational decision has implications for the estimation and interpretation of results. On the one hand, the profiles varied in the experiment become more realistic for respondents. On the other hand, however, averaged responses are based on less variation in attribute levels reflected in the experiment. To the extent that the population at large will shift and responses depend on attribute variation, the estimated results may be less valid and less reliable. Another methodological limitation of most studies is that blocking principles to avoid correlation between consumer attributes and the set of profiles or choice sets for which responses were obtained have not been applied.

Table 1 Overview of stated choice studies

Authors	Year	Vehicle type	Task	Design	# of attr.	Blocks	Choice sets	Model	Sample size	Time of data
Calfee	1985	*Electric* gasoline	Choice of second car	Random choice sets	5	N	30	MNL	51	1984
Bunch et al.	1993	Gasoline	Choice between 3 vehicle types	4^{21} Orthogonal fractional factorial design in 64 runs	5	N	4	MNL	1096	1991
		Alt fuel						NLM		
		Electric						MPM		
Brownstone	1996	Gasoline	Choice between 3 vehicle types	4^{21} Orthogonal fractional factorial design in 81 runs	7	N	6	MNL	2309	Jun–July 1993
		CNG, methanol and *electric*								
Brownstone and Train	1999							Mixed logit		
								With normal and lognormal distrib vars		
Ewing and Sarigöllü	1998	Current	Choice between 3 vehicle types	3^{15} Orthogonal fractional factorial design in 64 runs	8	Y	9	MNL	881	May 1994
		Alt fuel								
		Electric								
Dagsvik et al.	2002	Electric	Choice between 3 vehicle types	Maximum variation in attributes across individuals and choice sets, subject to realism	5	N	Rank 3 options in 15 sets	Varations of Luce model for rankings.	662	2001
		LP								
		Hybrid								
Adler et al.	2003	Gasoline	Choice between 3 vehicle types	4^{8} Orthogonal fractional design in 64 choice sets	6	Y	8	MNL	3333	
		Hybrid		+ 2^{6} endpoint design						
		Diesel								
Horne et al.	2005	Standard, natural gas, hybrid, hydrogen	Choice between 4	Choice set resolution IV design with random alignment of attribute levels	6	N	8	MNL	866	2002–2003
Potoglou and Kanaroglou	2007	Gasoline	Choice between 3	Pivoted 4^{13}	8	N	8	NML	482	March 21–April 30, 2005
		hybrid		Orthogonal fractional design in 64 choice sets						
		alt. fuel		+ 2^{13} endpoint design						

Table 1 (continued)

Authors	Year	Vehicle type	Task	Design	# of attr.	Blocks	Choice sets	Model	Sample size	Time of data
Mau et al.	2008	HEV resp	Binary choice	Pivoted 3^6	6	N	18	MNL	915 resp	2002
				Orthogonal fractional design in 18 choice sets						
		HFCV	for 4 segments of market penetrat.						1019	
Axsen et al.	2009	Gasoline	Choice of conv. vs HEV	Pivoted 3^7	5	N	18	MNL	535+408	March 2006
		Hybrid		Orthogonal fractional design in 18 choice sets						
Alvarez-Daziano Bolduc	2009	Gasoline natural gas, hybrid, hydro	Choice between 4	Choice set resolution IV design with random alignment of attribute levels	6	N	8	HCM	866	2002–2003
Mabit and Fosgerau	2011	Gasoline hydro	Binary choice between any two of five fuel types	Attributes varied indepen-dently from fuel type	6	N	12	ML with panel effects	2146	2007
		hybrid, bio-diesel, *electric*						With normal distrib vars		
Glerum et al.	2011	Gasoline	Choice of 3	Orthogonal fractional design in 54 choice sets	4	Y	16	HCM	1593	Early 2011
	2012	*electric*								
Achnicht	2012	Gasoline	Intention to buy	Pivoted $7\times5\times3^4$	6	N	6	MNL and mixed logit	600	Aug 2007–March 2008
		diesel, hybrid, LPG/CBG biofuel, hydro, *electric*		random fractional factor design				With normal and lognormal distrib vars		
Jensen et al.	2012	Gas or diesel vs *electric*	Binary choice	Pivoted $4^{14x}2$ orthogonal main-effects design in 64 runs	6	Y	8	HCM	372	2012
Rasouli & Timmerm.	2013	*Electric*	Binary Choice	$8^2\times4^9$ Orthogonal fractional factorial design in 128 runs	11	Y	16	MNL		June 2012
								ML		

The number and kind of attributes that have been included in previous stated choice models in this context have varied considerably as shown in Table 2. The numbers in the cells indicate the number of attribute levels that was varied in the experiment. An x means either that the number is not reported in the paper or a single value for a competing vehicle type is used. The kind of attributes can be distinguished between monetary attributes, attributes of the vehicle and contextual attributes. All stated choice studies included some measure of capital costs. Some studies explicated the absolute costs of the (electric) car and other vehicle types included in the study design. Other studies, particularly those that have applied a pivot, varied net capital cost as a function of some percentage difference from the purchase price of the current car. The exact definition of operating costs (another important monetary variable) differed slightly between the studies. Some included maintenance costs in this price, other separated maintenance costs. Similar to capital costs, some studies used absolute numbers for each vehicle type, whereas other studies used net operating costs. As for monetary costs, some policy-oriented studies separately explicitly included the subsidy level related to the alternative fuel vehicles (e.g., Mau et al. 2008; Axsen et al. 2009). Glerum and Bierlaire (2012) included the costs of battery lease. Thus, although these stated choice models differs somewhat in terms of the monetary attributes included in the experimental design, (net) capital costs and (net) operating costs have been used in all these studies.

Table 2 also gives an overview of the vehicle attributes that have been varied in previous studies. It shows that the majority of stated choice experiments have included cruising range, top speed/acceleration (sometimes split) and refueling time. Similar to the treatment of monetary variables, in some studies absolute values for one or more vehicle types were included, while in other studies attribute levels were specified in terms of differences between vehicle types. The majority of studies included engine power, whereas Axsen et al. (2009) included fuel efficacy.

As can also be seen in Table 2, very studies indeed incorporated contextual variables. Ewing and Sarigöllü (1998) included commuting time, expecting that the interest in purchasing non-gasoline cars may depend on commuter distance. They also included parking costs. Other studies have included warranty (Mau et al. 2008) and some specific incentives such as special lanes (Potoglou and Kanaroglou 2007a, b).

Although the problem of articulating preferences and intended choices for new, unfamiliar products is discussed in some of these papers, and it is acknowledged that market dynamics may influence individual choice behaviour, either this issue is not reflected at all in the study design or only incorporated in the general description of the experiment. For example, Axsen et al. (2009) randomly divided their sample into three treatment groups, which differed in terms of the scenario they received. In particular, these scenarios differed in terms of the penetration ratios of HEV (between 0.17 % and 50 %). To simulate consumer learning and the effects of word-of-mouth, each scenario also included hypothetical information from a newspaper, a manufacturer brochure and personal testimonials, communicating uncertainty about the technology and the availability of models. None of these studies have, however, systematically varied the market conditions and dynamics related to social influence.

In summary, then, although over the last decades the body of knowledge about consumer reactions to non-gasoline cars, including electric cars, has been systematically increased, prior studies exhibit some limitations, implying that further contributions to

Table 2 Overview of selected variables

Monetary attributes								
	Purchase price	Net capital costs	Subsidy	Fuel costs	Net operating costs	Costs other vehicles	Maintenance costs	Battery Lease
Achtnucht	3			3				
Adler et al.		4		4			4	
Axsen et al.	2×3		3	3				
Beggs et al.	4			4				
Brownstone		4			4	4		
Bunch et al.	4×3			4				
Ewing and Sarigöllü	3			3				
Horne et al.		4			4			
Mau et al.		3	3		3			
Potoglou and Kanaroglou		4		4	4			
Calfee	2			2				
Glerum et al.	3			3			3	3
Alvarez-Daziano		4			4			
Mabit Fosgerau	X			X			X	
Dagsvik et al.	X			X				
Jensen et al.	2			4		4		
Rasouli & Timmermans	8				8			
Vehicle and environmental attributes								
	Engine power	Fuel efficacy	Top Speed/acceleration	Grada-bility	Refueling Time	Cruising Range	Fuel availability	CO2 emissions
Achtnucht	3						3	5
Adler et al.			4	4				
Axsen et al.	3	2×3						
Beggs et al.			2+2		2	2		
Brownstone			4		4	4	4	4
Bunch et al.					4		4	4
Ewing and Sarigöllü			3		3	3		
Horne et al.	2 alt spec							3

Table 2 (continued)

Mau et al.						3	2	1 Alt spec
Potoglou and Kanaroglou			4				3	
Calfee			2			2	4	4
Glerum at al								
Alvarez Daziano	2 alt spec						2	1 Alt spec
Mabit Fosgerau			X		X	X		
Dagsvik			X			X		
Jensen			4		4	4	4×2	4
Rasouli & Timmermans			4		4	4	4	
Contextual attributes								
	Commuting Time	Fuel and parking costs	Warranty	Incentives	Air Conditioning	Number of seats	Reviews and social influence	
Achtnucht								
Adler et al.				4				
Axsen et al.								
Beggs et al.			2		2	2		
Bunch et al.								
Brownstone								
Ewing and Sarigöllü	3	3						
Horne et al.								
Mau et al.			3					
Potoglou and Kanaroglou				4				
Calfee				2				
Glerum at al								
Alvarez Daziano								
Mabit Fosgerau								
Dagsvik								
Jensen								
Rasouli & Timmermans							5×4	

this literature can be made. First, the number of attributes that has been varied in the experiments tends to be rather limited. As shown in Table 1, the vast majority of previous studies on the demand for alternative fuel cars have included only 4–6 attributes in their experimental design. Obviously, this limits the focus of the analysis and the kind of conclusions that can be drawn. In more extreme cases, the effects of non-included variables can be confounded with the estimated effects of the included variables. Second, transportation economics papers have primarily varied monetary variables, sometimes as a trade-off with particular vehicle attributes. Other papers have used a wider spectrum of non-monetary, vehicle and environmental attributes. In particular, contextual variables have been incorporated less. We could not find any studies that systematically varied the market share of electric cars among various elements of the social network of individuals. To the extent that social context plays an important role in the decision to buy an electric car, this is clearly a limitation. In any case, assessing the relative importance of social influence and reviews in the purchase decision constitutes an interesting research question. Third, most stated choice experiments on the topic at hand share some methodological limitations such as the lack of any blocking in experimental design, the possible impact of the use of pivoted designs on the generalizability of results, and the omission of panel effects in the estimation of the utility function.

The contribution of the present study, which elaborates previous research of the same authors (Rasouli and Timmermans 2013), to this body of knowledge is to (i) expand the number of potentially relevant attributes in the experiment; and (ii) estimate the effects of general reviews and social influence of different elements of social networks, while avoiding some potential methodological limitations, such as the lack of blocking, non-inclusion of panel effects, and use of pivoted experiments.

3 Design of the Experiment

3.1 Elicitation of Attributes and Attributes Levels

The first step in any stated choice experiment involves selecting attributes and attribute levels. Focus groups or other methods can be used to that effect, in particular when little is known about the factors influencing the choice behavior of interest. In the present study, it was decided not to conduct such qualitative research, but to use and expand the set of attributes that has been identified in previous qualitative research, discussed in Section 2, and included in previous stated choice experiments.

Table 3 lists the selected attributes and attribute levels. Selected attributes can be divided into vehicle attributes, contextual attributes and social influence attributes. In particular, the following attributes were systematically varied in the experiment: the net capital price of the electric car, net operating cost, cruising range of the car, the time required to (re-)charge the battery, the top speed of the car and the distance to a charging station. The social influence attributes describe possible reviews and adoption of this new technology by various elements of social networks (family, friends, colleagues and the larger social network of peers and the impact of the nature of reviews (positive or negative).

To allow for possible non-linear effects, while at the same time reducing the number of profiles, and enforcing the motivated desires of orthogonality and attribute

Table 3 Selected attributes and attribute levels

Attribute	Attribute level
Net capital price	35 % more expensive than gasoline
	25 % more expensive than gasoline
	15 % more expensive than gasoline
	5 % more expensive than gasoline
	5 % less expensive than gasoline
	15 % less expensive than gasoline
	25 % less expensive than gasoline
	35 % less expensive than gasoline
Net operative cost	35 % more expensive than gasoline
	25 % more expensive than gasoline
	15 % more expensive than gasoline
	5 % more expensive than gasoline
	5 % more expensive than gasoline
	15 % less expensive than gasoline
	25 % less expensive than gasoline
	35 % less expensive than gasoline
Cruising range of the car	100 km
	250 km
	400 km
	550 km
Time to charge battery	5 min change battery
	1 h charging battery
	4 h
	7 h
Max speed car	80 km/h
	120 km/h
	160 km/h
	200 km/h
Distance to charging stations	At home
	1 km
	5 km
	10 km
Reviews	Only positive reviews
	Mainly positive reviews but also some criticism
	Mainly negative criticism, but some positive
	Only negative reviews
Market share among friends	0 %
	25 %
	50 %
	75 %
Market share among relatives	0 %

Table 3 (continued)

Attribute	Attribute level
	25 %
	50 %
	75 %
Market share among colleagues	0 %
	25 %
	50 %
	75 %
Market share among peers	0 %
	25 %
	50 %
	75 %

balance, either four or eight levels were chosen to vary the levels of the selected attributes.

3.2 Design of Experiment

The combination of attributes and attribute levels, listed in Table 3, gives rise to an $8^2 \times 4^9$ full factorial design. It goes without saying that the number of choice sets (accept/do not accept choices) generated by this full factorial design would be overwhelming and impossible to complete by respondents. Therefore, an orthogonal fractional factorial design was created that also satisfies the conditions of orthogonality and attribute balance: the different attribute levels should appear proportionally in the experimental design. We argue that attribute balance is important to avoid the possibility that respondents would respond differently to the various attribute profiles, simply because some profiles and/or attribute levels are shown more often than others. Because the commercial software that was at our disposal did not allow constructing designs of this complexity, both in terms of the number of factors and the large number of attribute levels and/or did allow not constructing such designs with the attribute balance property, an orthogonal fractional factorial design of the $8^2 \times 4^9$ full factorial design in 128 runs was created from scratch. Attribute balance in this case means that the 8-level attributes appeared 16 times in the overall design, whereas the 4-levels attributes occur 32 times.

3.3 Construction of Response Task

The orthogonal fractional factorial design of the $8^2 \times 4^9$ full factorial was created such as to orthogonally block the experiment into 16 orthogonal subsets. Consequently, the blocks are independent of all attributes. It implies that any response bias will not systematically affect the evaluation and choice of attribute profiles varied in the blocks. Each respondent was shown all profiles of possible electric car profiles belonging to one of the blocks. Blocks were assigned randomly to respondents. In addition, attribute profiles were randomized within the blocks to avoid any fatigue effects. Respondents were asked to indicate, assuming that the electric car described by the listed combination of attribute levels would be on the market, whether they would buy it as respectively their first car, their second car or when renting a car. In this paper, only the choice (vs. no choice) of an electric car as a first car is analyzed.

The constructed design and response task implies that when deciding whether or not to accept the described electric car, respondents had to process and trade-off 11 attributes, which is a substantially larger number of attributes that commonly used in previous studies on the demand for electric and alternative fuel cars. It raises the question about the potential effects of task complexity on the validity and reliability of the responses. Potential problems of attribute selectivity, shifting focus during the experiment and simplifying response patterns have been well recognized in the relevant literature from the very beginning (e.g., Wright 1975; Green and Srinivasan 1978; Carson et al. 1994) and a wide set of recommendations and design strategies to minimize such effects have been suggested (Timmermans and Molin 2009). Hensher, Rose and their co-workers (e.g., Hensher 2004, 2006; Caussade et al. 2005; Hensher et al. 2006, 2007) have put the issue of task complexity and its potential effects on the judgment of profiles and choice behavior on the research agenda in transportation research. Mixed findings have been found. van de Vyvere et al. (1998), albeit in a housing context, found that estimated utilities between two designs differing in complexity were not statistically different. On the other hand, Arentze et al. (2003) and Hensher et al. (2006) did find evidence of effects of task complexity on responses. Based on this empirical evidence, we do not wish to deny that task complexity may be a serious issue and that some respondents may adopt simplifying strategies to reduce burden and completion times. Developing models that try to incorporate such mechanisms is on our research agenda (Zhu and Timmermans 2010). However, the results of a pilot study indicated that the task was doable; moreover, the constructed designs avoid that any fatigue effects have a systematic impact on estimated utilities.

3.4 Administration

The experiment was part of a larger survey, which also included questions about the history of vehicle holdings of the respondent, socio-demographic characteristics of the respondent and the household, and a set of attitudinal questions about electric cars. The survey was administered via Pauline, a platform develop by and for our group for the creation and administration of Web-based questionnaires. It is similar to commercial packages, but includes templates for more advanced options such as management of experimental designs, pictorial information, maps and animation.

Respondents were recruited through a commercial firm, which maintains a panel with known socio-demographics. These characteristics can be used to select or filter out particular segments of the population. In this study, only respondents with a driver’s license were recruited. The sample was a random sample of the panel, which in turn is said to be representative of the Dutch population.

The target sample size was 700 respondents. Data collection started Friday, June 8, 2012. By Sunday evening, the target of 700 respondents was surpassed. This shows the efficacy of the data collection process. The target sample size was achieved fast because panelists have committed to quickly completing questionnaires. Privacy of respondents was assured by setting up a connection between the company's firm and our Web application, filtering out their email addresses. Ultimately, 726 valid questionnaires were obtained after 926 potential respondents were contacted. This implies a response rate of 78.4 %, which is high compared to what is typically reported in the literature.

Our Web-based application allows checking the feasibility and consistencies of responses, implying that data cleaning after receiving the data is kept to a minimum. Responses are outputted to a format useable for subsequent analysis. Limdep was used to estimate the choice models.

4 Sample and Sample Characteristics

As indicated, the sample consists of 726 respondents. Table 4 details the frequency distribution of the selected socio-demographic characteristics. As shown in Table 4, 48.8 % of the sample was male, implying that 51.2 % was female. Age was categorized into six categories. Their frequency distribution in the sample was respectively 12.5 %, 16.8 %, 31.1 %, 28.9 %, 9.5 % and 1.2 %, indicating that all age categories are well

Table 4 Frequency distribution of socio-demographic characteristic

		Percentage
Gender	Male	48.80
	Female	51.20
Age	18–25	12.50
	26–35	16.80
	36–50	31.10
	51–65	28.90
	66–75	9.50
	>75	1.20
Marital status	Single	28.50
	Couples without children	31.60
	Couples children <12	27.60
	Couples children >12	22.30
Income	<650 Euro	11.70
	650≪1250	22.20
	1251≪1875	22.50
	1876≪2500	24.20
	>2500	16.40
Education	Elementary school	1.5
	Lower vocational school	9.20
	Middle general education	14.40
	Middle specialized education	11.00
	Middle vocational education	26.60
	Higher vocational education	26.20
	University	10.60
	Other	0.50

represented in the sample. Table 3 also shows that small households are overrepresented in the sample. Together, households with less than five people make up around 92 % of the sample. Singles and married respondents without children represent a slightly larger percentage than 60 %. Almost 30 % does not have a paid job, while a large percentage works part-time. As for education, the sample is quite mixed, with a relatively low number of respondents with high education and the majority of the respondents with middle level education.

5 Mixed Logit Model

5.1 Introduction

The constructed experimental design yielded 726×16=11616 data points for estimating the latent demand for electric cars. As shown in the literature review, most previous research has applied the multinomial logit model, but more recently the mixed logit model has become dominant to account for the effects of unobserved heterogeneity. In the context of electric cars, such effects may be prevalent, considering for example the possibility that respondent may differ in terms of their attitudes towards green mobility. In line with this recent trend, the mixed logit model is also used in this study to estimate the effects of the selected attributes and social influence on the probability of choosing an electric car. Because each respondent was requested to provide a response to a set of 16 profiles, panel effects were also included. The results of the simpler MNL model are reported elsewhere (Rasouli and Timmermans 2013).

The mixed logit model can be derived from random utility theory (Train 2003). Assume that the utility U_{njt} that individual n ($n \in \{1,.., N\}$) chooses option j ($j \in \{1,.., J\}$ in choice set t ($t \in \{1,.., T\}$ is equal to

$$U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt} \tag{1}$$

where x_{njt} is the vector of attributes of the option and socio-demographic of the individual and ε_{njt} is a iid extreme value error term. In the classic MNL model, the vector β'_n consists of fixed-point estimates for the effects of the attributes and socio-demographic variables. By assuming that the error terms are iid Gumbel distributed, the MNL is given by

$$p_{nj} = \frac{\exp\left(\beta' \mathbf{x}_{nj}\right)}{\sum_{j'} \exp\left(\beta' \mathbf{x}_{nj'}\right)} \tag{2}$$

Whereas the MNL model assumes fixed point estimates, the mixed logit model allows these estimates to vary across individuals according to some specified density function to represent heterogeneity. This is accomplished by partitioning the error term into two additive, uncorrelated components. Thus,

$$U_{njt} = \beta'_n x_{njt} + \left[\eta_{njt} + \varepsilon_{njt}\right] \tag{3}$$

where η_{njt} is a random term with zero mean whose distribution across individuals and choice alternatives and ε_{njt} is a random term with zero mean that is iid distributed across choice alternatives. The mixed logit model assumes a general distribution for η with density distribution $f(\eta|\Omega)$, where Ω are the fixed parameters of the distribution, and an iid extreme value distribution for ε. The choice probability η_{njt} of option j being chosen is given by

$$p_j = \int \frac{\exp\left(\beta' \mathbf{x}_j + \eta_j\right)}{\sum_{j'} \exp\left(\beta' \mathbf{x}_{j'} + \eta_j\right)} f(\eta|\,\Omega) d\eta \tag{4}$$

Because respondents were asked to accept or decline the electric car of the given attribute profile under some market conditions, the dependent variable is a dichotomous variable, Eq. (4) can be reduced to the binary mixed logit model:

$$p_j = \int \frac{1}{1 + \exp\left(\beta' \mathbf{x}_j + \eta_j\right)} f(\eta|\,\Omega) d\eta \tag{5}$$

The specification of the mixed logit model requires a decision regarding the form of the density function. Previous studies have either assumed a normal or a lognormal density function. In this study, we decided to capture heterogeneity in terms of a normal density function. Because the number of variables is high, and we encountered estimation problems when trying to estimate random effects for all variables, two different mixed logit models were estimated: (1) a mixed logit model with the vehicle and contextual attributes as random effects and the remaining attributes as non-random effects, and (ii) a mixed logit model with the vehicle and contextual attributes as non-random effects and the remaining attributes as random effects. Because respondents provided answers to a block of 16 choice options, panel effects were also included in the model.

The primary aim of the analysis was to estimate the probability that individuals will choose an electric car as their first car, depending on the vehicle attributes, social influences and a set of socio-demographic characteristics. Because respondents were asked to indicate about their purchase intention to buy an electric car of the given profile and set of conditions in their social network or not, their current gasoline car was only implicitly mentioned and its attributes were not systematically varied in the experiment, the utility of the current car was set at 1, implying that a mixed binary logit model with panel effects was estimated. Effect coding was used to represent the various attribute levels. That is, for L attribute levels, L-1 indicator variables were constructed. Each attribute level was coded 1 on the corresponding indicator variable and 0 on all L-1 indicator variables. The base profile, in this study the last attribute level for all attributes, was coded −1 on all indicator variables. Consequently, estimated coefficients should be interpreted as deviations of the utility of the corresponding attribute level from the overall mean utility. Logically, significance test indicate whether these deviations from the overall mean utility are significantly larger than zero. The effects of inherently continuous variables were also estimated using discrete categories to allow greater flexibility in the curvature of the corresponding utility function.

5.2 Mixed Binary Logit Model with Random Effects for Vehicle and Contextual Attributes and Non-random Effects for Social Influence

5.2.1 Estimated Effects for Vehicle Attributes

The estimation results of the model estimation are listed in Table 5, part 1. The goodness-of-fit of the model is satisfactory as indicated by 87.7 % correctly predicted stated choices. McFadden pseudo R-square is 0.349. Table 5 shows that the signs of virtually all estimated coefficients are in line with theoretical expectations. Note that virtually all vehicle attributes are significantly different from zero (mean utility) due to high positive or negative part-worth utilities and/or small standard errors. The estimated coefficients for net capital price of an electric car compared to the price of the same car but with a gasoline engine monotonically increase with increasing price differences. the only exception being a 35 % lower price category.

Table 5 also indicates that if the net operations costs for the electric car are negative, utility tends to more or less monotonically increase. If these costs are positive, utility for the electric car is substantially lower. If the difference is between 5 % and 15 % when the electrical car net cost is more part-worth utilities are approximately the same; surprisingly, it is less low when the positive difference is 25 %.

As for the vehicle attributes, Table 5 shows that utility rapidly increased with increasing cruising range until approximately 400 km. The effect of this attribute on utility is negative if the range is below approximately 200 km. The estimated part-worth utility for time needed to charge the battery is monotonically decreasing with increasing charging time. Utility drops fast after 5 min, but tends to stabilize around 4 h. The estimated part-worth utility curve for the top speed of an electric car is negative for a speed of 80 km/h. Estimated utility increases with higher speed, but decreases again for very high speeds, suggesting that respondents are not really interested in very high maximum speeds for the electric car. As for the distance to charging stations, estimated coefficients suggest that utility is more or less the same for a distance under 1 km, and then decreases with increasing distance.

5.2.2 Estimated Scale Parameters for Monetary and Vehicle Attributes

Table 5, part 2 lists the estimated parameters of the assumed normally distributed density function for the random effects. As expected, it shows that the standard deviation is smaller for the middle levels of the net capital price of the electric car. Interestingly, the estimated standard deviation is very high for the two highest capital price categories for which the electric car is much more expensive than a conventional car, based on gasoline. The standard deviation is much lower for the other extremes where the electric car is cheaper. These suggest that heterogeneity is relatively small in case the electric car is substantially cheaper. There is, however, significant variation if the electric car is considerably more expensive. This suggest that the choice of some respondents may be primarily driven by environmental concerns, and they might still consider buying an electric car even if it would be more expensive than a car based on gasoline. In general, heterogeneity seems much lower in case the capital price of an electric car is lower. Similar results are obtained for net operational costs. Heterogeneity as depicted by standard deviations is more or

Table 5 Estimated parameters model I

	Random Parameters	Coefficient	St. Error	*p*-value
	Constant	−2.4649	0.1381	0.0000
Net capital costs	35 % more expensive than gas	−3.2339	0.1356	0.0000
	25 % more expensive than gas	−1.4614	0.1423	0.0000
	15 % more expensive than gas	−1.003	0.1297	0.0000
	5 % more expensive than gas	0.7417	0.1335	0.0000
	5 % less expensive than gas	1.4249	0.1416	0.0000
	15 % less expensive than gas	1.6591	0.1448	0.0000
	25 % less expensive than gas	2.0289	0.131	0.0000
	35 % less expensive than gas	−0.1563		
Net operating costs	35 % more expensive than gas	−3.2846	0.1373	0.0000
	25 % more expensive than gas	−1.0555	0.1374	0.0000
	15 % more expensive than gas	−2.1311	0.1268	0.0000
	5 % more expensive than gas	−2.1328	0.1347	0.0000
	5 % less expensive than gas	1.9407	0.1342	0.0000
	15 % less expensive than gas	1.3841	0.1305	0.0000
	25 % less expensive than gas	2.6784	0.1369	0.0000
	35 % less expensive than gas	2.6008		
Cruising range	100 km	−2.1828	0.0889	0.0000
	250 km	0.3399	0.0873	0.0001
	400 km	1.0287	0.0866	0.0000
	550 km	0.8142		
Time to charge the battery	5 min	0.7995	0.0907	0.0000
	1 h	−0.0098	0.0922	0.9194
	4 h	−0.3954	0.0978	0.0001
	7 h	−0.3943		
Max speed car	80 km/h	−1.3012	0.0857	0.0000
	120 km/h	0.3331	0.0954	0.0005
	160 km/h	0.607	0.0919	0.0000
	200 km/h	0.3611		
Distance to charging station	At home	0.1781	0.0915	0.0517
	1 km	0.2478	0.0924	0.0074
	5 km	−0.0591	0.1028	0.5654
	10 km	−0.3668		
Scale parameters of random parameters				
		Coefficient	St. Error	*p*-value
	Constant	4.7839	0.0908	0.0000
Net capital costs	35 % more expensive than gas	4.1582	0.1523	0.0000
	25 % more expensive than gas	5.4252	0.1887	0.0000
	15 % more expensive than gas	1.1199	0.1287	0.0000
	5 % more expensive than gas	1.3470	0.1470	0.0000
	5 % less expensive than gas	0.7248	0.1411	0.0000
	15 % less expensive than gas	1.1872	0.1463	0.0000

Table 5 (continued)

	25 % less expensive than gas	0.4740	0.1442	0.0001
	35 % less expensive than gas			
Net operating costs	35 % more expensive than gas	4.2210	0.1913	0.0000
	25 % more expensive than gas	4.0824	0.1761	0.0000
	15 % more expensive than gas	1.4706	0.1518	0.0000
	5 % more expensive than gas	3.8858	0.1750	0.0000
	5 % less expensive than gas	0.1556	0.1433	0.2775
	15 % less expensive than gas	1.0709	0.1390	0.0000
	25 % less expensive than gas	0.4394	0.1503	0.0035
	35 % less expensive than gas			
Cruising range	100 km	7.0155	0.1847	0.0000
	250 km	1.2383	0.1106	0.0000
	400 km	0.0593	0.1072	0.5797
	550 km			
Time to charge the battery	5 min	0.6393	0.1081	0.0000
	1 h	0.1926	0.1002	0.0547
	4 h	0.2118	0.1171	0.0705
	7 h			
Max speed car	80 km/h	0.9722	0.1123	0.0000
	120 km/h	1.3737	0.1116	0.0000
	160 km/h	0.3607	0.1128	0.0014
	200 km/h			
Distance to charging station	At home	0.1574	0.1024	0.1243
	1 km	1.0048	0.1346	0.0000
	5 km	0.2527	0.1373	0.0658
	10 km			
	Non-random Parameters (social influence)	Coefficient	St. Error	*p*-value
Reviews	Only positive reviews	0.5244	0.0947	0.0000
	Mainly positive reviews but also some criticism	0.3354	0.0931	0.0003
	Mainly negative reviews but also positive	0.0397	0.0947	0.6745
	Only negative reviews	−0.8995		
Share friends	0 %	0.1695	0.0945	0.0727
	25 %	−0.0314	0.0925	0.7346
	50 %	0.3534	0.095	0.0002
	75 %	−0.4915		
Share relatives	0 %	−0.0456	0.0998	0.648
	25 %	−0.0902	0.0929	0.3317
	50 %	0.0227	0.0971	0.8148
	75 %	0.1131		
Share colleagues	0 %	0.2537	0.0943	0.0071
	25 %	0.1604	0.0996	0.1073

Table 5 (continued)

	50 %	−0.0729	0.1007	0.4693
	75 %	−0.3412		
Share peers	0 %	−0.0633	0.0908	0.4858
	25 %	0.0900	0.0946	0.3416
	50 %	0.8600	0.0907	0.3434
	75 %	−0.8867		
	Non-random Parameters (socio-economic)	Coefficient	St. Error	*p*-value
Gender	Male	−0.0929	0.0341	0.0064
	Female	0.0929		
Age	18–25 years of age	0.2372	0.1413	0.0933
	26–35 years of age	0.9232	0.1331	0.0000
	36–50 years of age	0.0301	0.1234	0.807
	51–65 years of age	0.0869	0.1245	0.485
	66–75 years of age	1.1702	0.1372	0.0000
	>75 years of age	−2.4476		
Marital status	Single	−0.0808	0.0611	0.1864
	Couple without children	−0.5896	0.0594	0.0000
	Couple with children <12	0.8877	0.0744	0.0000
	Couple with children >12	−0.2173		
Education	Elementary school	−0.1581	0.3429	0.6448
	Lower vocational school	−0.9994	0.153	0.0000
	Middle general education	−0.4419	0.1184	0.0002
	Middle specialized education	0.2366	0.1212	0.051
	Middle vocational education	−0.0697	0.1046	0.5049
	Higher vocational education	0.4368	0.1069	0.0000
	University	−0.7327	0.1212	0.0000
	Other	1.7284		
Income	< 625 Euros/month	−0.6132	0.9200	0.0000
	625–1.250 Euros/month	0.1178	0.0746	0.1142
	1.251–1.875 Euros/month	−0.2109	0.0618	0.0006
	1.876–2.500 Euros/month	0.4063	0.0648	0.0000
	> 2.500 Euros/month	0.3000		

less the same for the net operating cost categories in both regimes (electrical car more expensive and electrical car less expensive)

As for vehicle attributes, estimated standard deviations of the assumed normal distribution of the estimated part-worth utilities for cruising range systematically decrease from low to higher cruising ranges. For a range up to 100 km, the standard deviation is very high, again suggesting that some respondents are truly interested in buying an electric car, regardless of its performance, including cruising range, whereas others will not consider buying an electric car if the cruising range is less than 100 km. Heterogeneity is very small and not significant if the cruising range is 400 km. It is also relatively small for the time to charge the battery variable.

Moreover, the estimated standard deviations are higher for the short time category. They are lower and not significant for the categories involving more time to charge the battery. As for the top speed variable, results suggest that respondents differ more widely in their utility and underlying choice behavior if the top speed is lower. The estimated standard deviation first slightly increases from 80 km/h to 120 km/h and then decreases again from 120 km/h to 160 km/h.

Finally, Table 5 reports the estimated standard deviations of the assumed normal density function for the categories of the distance to charging station variable. Heterogeneity is small and insignificant for the at home and the 5 km distance categories. It is higher and significant for the 1 km category.

5.2.3 Estimated Coefficients for Social Influence Parameters

The second subset of attributes varied in the experiment related to social influence as measured in terms of market shares of the electric car for various elements of people's social network (i.e. friends, relatives, colleagues and peers) and general public reviews. As discussed in the literature review section, it is this set of attributes that differentiates the present study from previous stated choice studies. The results of the estimated non-random effects for these attributes are reported in Table 5, part 3. It shows that the part-worth utility of reviews, differing from positive to negative, monotonically decreases from more positive to more negative categories. Estimated part-worth utility is decreasing at an increasing rate as the reviews become more negative.

Four different kinds of members were identified, being friends relatives, colleagues and peers. Several interesting results were found. First, for relatives and peers the effect of social influences are not statistically significant for the current sample size. Second, the curvature of the estimated part-worth utility functions shows small, but interesting, differences between different elements of the social network. In case of friends, the estimated part-worth utility behaves like the edge of a knife: it goes up and down between adjacent market share levels. For relatives, after a decrease, estimated part-worth utility increases with increasing market shares. In contrast, estimated part-worth utilities monotonically decrease with increased market share among colleagues. Finally, estimated part-worth utilities for market penetration among peers show evidence of satiation.

5.2.4 Estimated Coefficients for Socio-Demographic Characteristics

Table 5, part 4 shows that females are more positively inclined to buy an electric cars than men are, although differences between estimated utilities are small, but significant. The effects of the age categories suggest that the utility for an electric car is higher for respondents younger than 35 years of age and lower beyond that age, except for the 65–75 age category. As expected, estimated effects for the elderly are highly negative. The effects of marital status indicate that in particular households with young children are positively inclined to buy an electric car. As for the effects of education, Table 5 shows that the estimated utility for an electric car is higher for respondents with a degree in higher vocational education and middle specialized education. Finally, the estimated effects for income suggest that utility for an electric care is low for the lowest income group. It is highest for the two highest income groups.

5.3 Mixed Binary Logit Model with Random Effects for Social Influence and Non-Random Effects for Vehicle and Contextual Attributes

The second estimated model differs from the first model in that the fixed and random variables have been reversed between the social influence attributes and the other attributes. Thus, model II examines the impact of heterogeneity in the selected social influence variables on overall goodness-of-fit of the binary logit model with panel effects and on the estimated coefficients. The estimation results for this model are reported in Table 6. The goodness-of-fit of the model is satisfactory as indicated by 86.30 % correctly predicted stated choices. McFadden pseudo *R*-square is 0.308. Compared to Model I., this goodness-of-fit result implies that the model allowing heterogeneity in social influence performs substantially less well than the model allowing for heterogeneity in monetary and vehicle attributes.

5.3.1 Estimated Coefficients for Social Influence Parameters

Table 6, part 1 lists the estimated effects for the subset of attributes measuring the influence of different elements of social network and general public reviews. It shows that the estimated part-worth utility of reviews monotonically decreases from more positive to more negative reviews. The function is almost linear, but then drops for the category “only negative reviews”.

Similar to Model I, the estimated part-worth utilities for sources of social influence differ, both in curvature and absolute size. The influence seems highest for friends and lowest for colleagues. Estimated coefficients first increase with increasing market shares of electric cars among friends and then substantially drop for the 75 % category. In case of relatives, the estimated utility exhibits the following pattern: it increases with increasing market share to satiate at 50 %. The curvature for colleagues is first monotonically decreasing with increasing market share of the electric car among colleagues, and then increases again when the market share is high. Finally, the curve for peers shows that estimated part-worth utilities decrease with increasing market shares of electric cars among peers and then slightly increases again, although it remains negative for the highest market share category.

5.3.2 Estimated Scale Parameters for Social Influence Attributes

Table 6, part 2 lists the estimated parameters of the assumed normally distributed density function for the random effects of the social influence attributes. It shows that for the reviews the standard deviation is slightly increasing when the reviews become more negative. Estimated standard deviations vary more widely for the effects of different members of the social network. In case of friends, heterogeneity is highest when market share of the electric car is 25 %. The scale parameter shows a less extreme distribution in case of relatives. It first increases from zero market share to 25 % market share, and then drops when the market share of the electric car among relatives is 50 %. The estimated standard deviations for heterogeneity in the effect of colleagues shows more variation when the share is zero per cent and less variation when the shares are respectively 25 and 50 %. Finally, Table 6 shows that the estimated standard deviation of the assumed normal distribution monotonically

Table 6 Estimated parameters Model II

	Random Parameters	Coefficient	St. Error	*p*-value
	Constant	−2.7686	0.1295	0.0000
Reviews	Only positive reviews	1.0173	0.0883	0.0000
	Mainly positive reviews but also some criticism	0.5380	0.0806	0.0000
	Mainly negative reviews but also positive	−0.1266	0.0834	0.1291
	Only negative reviews	−1.4287		
Share friends	0 %	0.1047	0.0826	0.2051
	25 %	0.1881	0.0823	0.0222
	50 %	0.5365	0.0795	0.0000
	75 %	−0.8293		
Share relatives	0 %	−0.3063	0.0833	0.0002
	25 %	−0.0609	0.0855	0.4767
	50 %	0.1847	0.0818	0.0239
	75 %	0.1825		
Share colleagues	0 %	0.0665	0.0879	0.4492
	25 %	0.0015	0.0795	0.9846
	50 %	−0.2055	0.0851	0.0157
	75 %	0.1375		
Share peers	0 %	0.3203	0.0842	0.0001
	25 %	0.1009	0.0851	0.2358
	50 %	−0.2640	0.0822	0.0013
	75 %	−0.1572		
Scale parameters of random parameters				
	Random Parameters	Coefficient	St. Error	*p*-value
	Constant	4.4489	0.0845	0.0000
Reviews	Only positive reviews	2.0717	0.1099	0.0000
	Mainly positive reviews but also some criticism	2.5394	0.1104	0.0000
	Mainly negative reviews but also positive	2.8141	0.1118	0.0000
	Only negative reviews			
Share friends	0 %	0.9345	0.0977	0.0000
	25 %	4.0219	0.1167	0.0000
	50 %	0.4502	0.0951	0.0000
	75 %			
Share relatives	0 %	1.2897	0.1027	0.0000
	25 %	1.4456	0.0975	0.0000
	50 %	0.5762	0.0889	0.0000
	75 %			
Share colleagues	0 %	1.6388	0.1069	0.0000
	25 %	0.7983	0.0895	0.0000
	50 %	0.4060	0.0943	0.0000
	75 %			

Table 6 (continued)

Share peers	0 %	0.7934	0.093	0.0000
	25 %	0.9640	0.1058	0.0000
	50 %	2.8347	0.1128	0.0000
	75 %			
	Non-random Parameters (vehicle attributes)	Coefficient	St. Error	*p*-value
Net capital price	35 % more expensive than gas	−2.5367	0.1186	0.0000
	25 % more expensive than gas	−1.0048	0.1171	0.0000
	15 % more expensive than gas	−1.3231	0.1161	0.0000
	5 % more expensive than gas	0.5976	0.122	0.0000
	5 % less expensive than gas	0.3710	0.1249	0.0030
	15 % less expensive than gas	1.1793	0.1198	0.0000
	25 % less expensive than gas	1.8008	0.1248	0.0000
	35 % less expensive than gas	0.9159		
Net operating costs	35 % more expensive than gas	−2.2541	0.1211	0.0000
	25 % more expensive than gas	−1.0685	0.1229	0.0000
	15 % more expensive than gas	−2.2150	0.1186	0.0000
	5 % more expensive than gas	−1.9478	0.1235	0.0000
	5 % less expensive than gas	1.5064	0.1175	0.0000
	15 % less expensive than gas	1.3776	0.1189	0.0000
	25 % less expensive than gas	2.3111	0.1224	0.0000
	35 % less expensive than gas	2.2903		
Cruising range	100 km	−1.4127	0.0749	0.0000
	250 km	−0.0648	0.0705	0.3579
	400 km	0.4616	0.0776	0.0000
	550 km	1.0159		
Time to charge the battery	5 min	0.7217	0.0816	0.0000
	1 h	0.1589	0.0801	0.0473
	4 h	−0.2466	0.0785	0.0017
	7 h	−0.634		
Max speed car	80 km/h	−1.6313	0.0737	0.0000
	120 km/h	0.5208	0.0827	0.0000
	160 km/h	0.5036	0.0851	0.0000
	200 km/h	0.6069		
Distance to charging station	At home	0.248	0.0805	0.002
	1 km	0.2274	0.0773	0.0033
	5 km	−0.1421	0.0806	0.0781
	10 km	−0.3333		
	Non-random Parameters (socio-economic)	Coefficient	St. Error	*p*-value
Gender	Male	0.1810	0.0314	0.0000
	Female	−0.1810		
Age	18–25 years of age	−0.2093	0.1166	0.0728
	26–35 years of age	0.4807	0.1071	0.0000

Table 6 (continued)

	36–50 years of age	0.1081	0.1007	0.2829
	51–65 years of age	−0.4516	0.0991	0.0000
	66–75 years of age	0.3103	0.1200	0.0098
	>75 years of age	−0.2382		
Marital status	Single	0.5883	0.0554	0.0000
	Couple without children	−0.2044	0.0521	0.0001
	Couple with children <12	0.1824	0.0643	0.0046
	Couple with children >12	−0.5663		
Education	Elementary school	−0.2732	0.2581	0.2899
	Lower vocational school	−0.8602	0.1452	0.0000
	Middle general education	−0.2833	0.1198	0.0181
	Middle specialized education	0.9712	0.1211	0.0000
	Middle vocational education	0.167	0.1102	0.1296
	Higher vocational education	0.399	0.1100	0.0003
	University	−0.1011	0.1226	0.4096
	Other	−0.0194		
Income	< 625 Euros/month	−0.6308	0.084	0.0000
	625–1.250 Euros/month	−0.1992	0.0665	0.0027
	1.251–1.875 Euros/month	0.157	0.0581	0.0069
	1.876–2.500 Euros/month	0.9773	0.0576	0.0000
	> 2.500 Euros/month	−0.3043		

increases in case of increasing market share of the electric car among peers which is the reverse of the colleagues pattern. Most random effects are highly significant.

5.3.3 Estimated Effects for Vehicle Attributes

Compared to Model I, Table 6, part 3 shows that fewer signs of the estimated coefficients are in line with theoretical expectations. The estimated coefficients for the net capital price of an electric car compared to the price of the same car but with a gasoline engine are not monotonically related to increasing price differences, not in the positive domain and not in the negative domain. Only if we would ignore the estimated coefficients for some attribute levels, estimated part-worth utilities tend to decrease when the electric car becomes relatively more expensive, and increases if it becomes relatively less expensive. As in case of Model I, the utility curve is not symmetrical between the two regimes: it is steeper when the electric car is more expensive relative to the gasoline car.

Table 6 also indicates that if the net operating costs for the electric car are negative, estimated utility is significantly higher. If the difference is between 5 % and 15 % when electrical car cost is less, estimated part-worth utilities are approximately the same; the same is true for the 25 % and 35 % categories, although in this case, the estimated utilities are higher.

As for the vehicle attributes, Table 6 shows that estimated utilities increase with increasing cruising range; the curve is however less steep than the estimated curve for this attribute in model I. The effect of this attribute on utility is negative if the range is below approximately 300 km. The estimated part-worth utility for time needed to charge the battery is monotonically decreasing with increasing charging time. The estimated part-worth utility curve for the top speed of an electric car is negative for a speed of 80 km/h, and positive and virtually the same when the top speed is higher than 120 km/h, suggesting that respondents do not prefer a high top speed when buying an electric car. As for the distance to charging stations, estimated coefficients suggest that utility is more or less the same for a distance under 1 km, and then decreases with increasing distance; a results similar to the result for Model I.

5.3.4 Estimated Coefficients for Socio-Demographic Characteristics

Table 6, part 4 exhibits the effects of the selected socio-demographic variables. For this model, men are more positively inclined to buy an electric car than women. The effects of the age categories suggest that the utility of an electric car is higher for respondents between 25 and 35 years of age and between 65 and 75 old, suggesting a higher propensity to buy an electric car. Estimated effects are lowest for the youngest and oldest age categories and the 51–65 years of age category. The effects of marital status indicate that in particular households with young children are positively inclined to buy an electric car, a finding that was also obtained for Model I. As for the effects of education, Table 6 shows that the estimated utility for an electric car is higher for respondents with a degree in higher vocational education and middle specialized education, and to some extent also for middle vocational education. Finally, the estimated effects for income suggest that utility for an electric car monotonically increases with increasing monthly income, except for the highest income category.

5.4 Comparison of Model I and Model II

To visually compare the two models Figs. 1 and 2 portray the estimated part-worth utilities of Model I and II. Figure 1 shows that for monetary and contextual attributes, the estimated part-worth utilities of the two models are almost the same. There are some small differences. For example, estimated part-worth utilities are higher for Model I when the net capital cost of an electric car is 5 and 15 % less than the costs of a gasoline car. Moreover, in model I, the difference in estimated utility between the second and third level of the cruising range attribute is higher. Model I also estimated a lower sensitivity to the time to charge the battery.

Examining Fig. 2 reveals that the difference between two models is more significant for social influence. Model II shows that with an increasing share of electric cars among friends estimated utility increases up to 50 % and then decreases, while model I estimates a decrease in part-worth utility for the second level of this attribute. In case of relatives, again model II shows a monotonically increasing utility function with market share among relatives increasing up to 50 %, followed by a decrease in utility. In contrast, model I first predicts a decrease in utility with increasing market and then monotonically increasing utility. There also is a difference in the shape of the estimated utility function between the two models for the share of electric cars among colleagues. The estimated part-worth utility function of Model I is higher than the estimated function of Model II for the first three attribute levels, although the differences decrease with increasing levels.

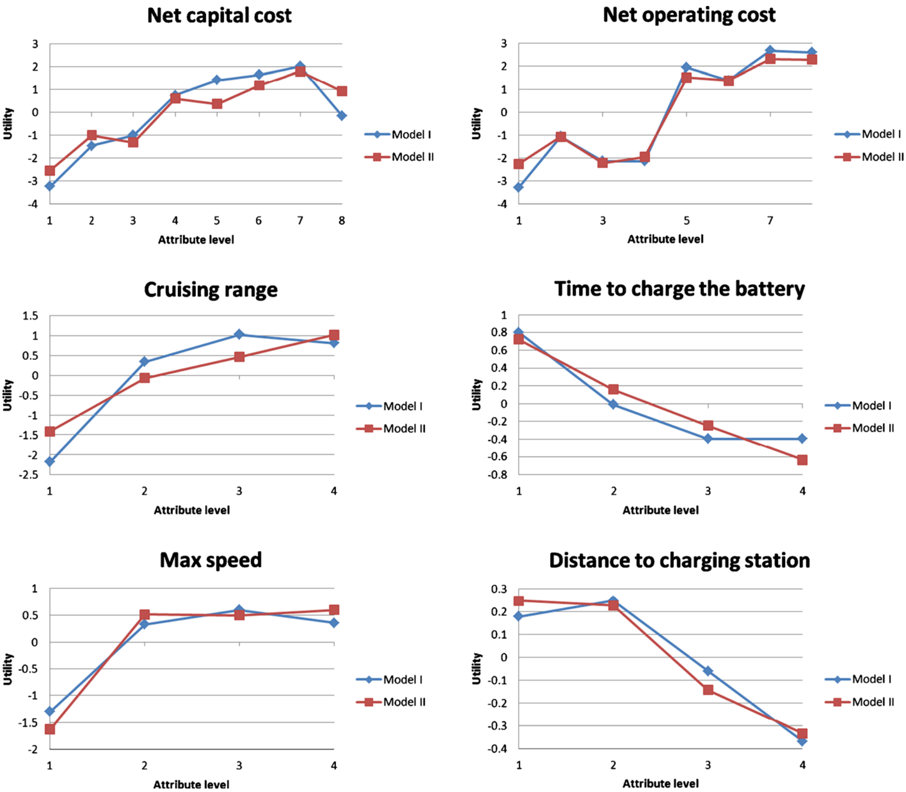

Fig. 1 Comparison model I II (estimated part-worth utilities monetary and contextual attributes)

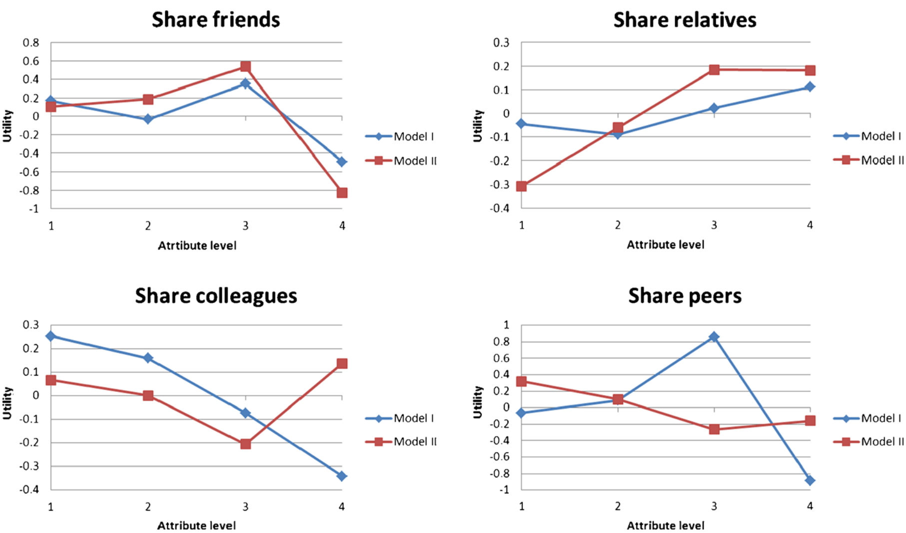

Fig. 2 Comparison model I and II (estimated part-worth utilities Social influence attributes)

However, the estimated part-worth utility for the fourth level in Model I continues to decrease, while the corresponding part-worth utility of Model II increases substantially, creating a significant different for the highest share of electric car among colleagues. The most extreme difference between model I and II is related to the share of electric cars peers: estimate utilities show an inverse pattern of increasing/decreasing utilities. Model II indicates this social influence attribute to be more important that Model I suggests, as demonstrated by the higher difference in estimated part-worth utilities.

6 Conclusions and Future Study

Arguing that a significant reduction of noise and pollution depends on new clean technology in the automotive industry, it is paramount that a larger share of the population accepts new technology such as the electric car. Early studies have suggested that the market share of such cars has traditionally been quite small and insignificant in light of the enormous environmental problems. The quality of electric cars has, however, improved considerably lately, stimulating a new recent wave of research on the latent demand for electric cars and other alternative fuel vehicles.

The aim of this study is to contribute to this rapidly emerging new wave of studies in a variety of ways. First and foremost, although it is well-known that innovation and diffusion processes of modern technology are often strongly influenced by social networks, we are not aware of any previous research on electric cars that has systematically examined the relative effects of different members of social networks on the latent demand of electric cars. Thus, a major contribution of the current study to the existing body of knowledge on the acceptance of electric cars concerns the inclusion of social influence. Second, compared to previous research, this study includes a wider set of variables in the construction of the experimental design.

Mixed logit models are estimated to assess the effects of vehicle, contextual and social network attributes and a set of socio-demographics on the choice of electric cars. Because the number of attributes is high, two different models were estimated: one allowing for random effects for social influence attributes, the second model allowing for random effects for the vehicle and contextual attributes. Results differ, not only in size but also in nature between these two models. Overall, however, the acceptance of the electric car primarily depends on the relative costs of the electric car and its attributes. Social influence plays a minor role. Different members of social networks (family vs. friends vs. colleagues vs. peers) have a different impact in the sense that market shares of electric cars in these social networks might stimulate individuals to buy an electric car or conversely reduce their desire to act as these members of their social network do..

Although the complexity and therefore sensitivity of these models exceeds that of previous models, still some further more complex specifications can be examined in future work. First, the random effects of the various attributes are independent. However, one cannot rule out that unobserved variables exert similar effects on related attributes, such as for example monetary attributes. Correlations between random effects could therefore be estimated in future research. Second, a fundamental limitation of mixed logit models is that it deals with unobserved variables. It would be better to try expanding the set of measured variables, such as environmental attitudes. This extension should be attempted in future research applying the hierarchical choice model or more general latent structural equations models. Third, the current model only estimates the main effects of socio-demographic variables. However, these variables may have a differentiating impact on the different attributes. Hence, it may be interesting to estimate interaction effects in possible further improvements of the model. Finally, to explore the dynamics of evolving markets it would be interesting to use the results of the model in agent-based simulations of travel demand (e.g. Flötteröd et al. 2012) and multi-state supernetwork models of activity-travel scheduling (e.g., Arentze and Timmermans 2004; Ramadurai and Ukkusuro 2010; Liao et al. 2010, 2011).. At the start of the simulation, the latent demand for electric cars with zero market shares would be predicted. This would result in an estimated market share for the different elements of the social network. Given these market shares, new demand would be simulated and this process can be iterated until stable market conditions would be reached or the set time horizon has been simulated. We intend to report on such elaborations in future publications.

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