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Assessing the Impact of Direct Experience on Individual Preferences and Attitudes for Electric Vehicles

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PhD Thesis

Anders Fjendbo Jensen

August 2014

DTU Transport
Department of Transport

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PREFACE

This PhD thesis entitled *Assessing the impact of direct experience on individual preferences and attitudes for electric vehicles* is submitted to meet the requirements for obtaining a PhD degree at the Department of Transport, Technical University of Denmark. The PhD project was supervised by Elisabetta Cherchi, Associate Professor at DTU Transport and co- supervised by Stefan Lindhard Mabit, Associate Professor at DTU Transport and Juan de Dios Ortúzar, Professor at Pontificia Universidad Católica de Chile. The thesis consists of the following chapters and the papers listed below.

Paper 1: Jensen, A. F., Cherchi, E., & Ortüzar, J. de D. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation*, Published Online First DOI: 10.1007/s11116-014-9517-6.

Paper 2: Jensen, A.F.; Cherchi, E., & Mabit, S.L. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment*, *25*, 24-32.

Paper 3: Jensen, A.F. and Cherchi, E. (2014). Exploring different sources of variation in individual preferences for electric vehicles. *Working paper*, DTU Transport.

Paper 4: Jensen, A.F., Cherchi, E., Mabit, S.L. & Ortúzar, J. de D. Predicting the potential market for electric vehicles. *Working paper*, DTU Transport.

The following article was also submitted during my PhD period, and deals with the general topic of the PhD, however, it is not presented as part of the thesis:

Mabit, S.L., Cherchi, E., Jensen, A.F. & Jordal-Jørgensen, J. Hybrid Choice Modelling Allowing for Reference-dependent Preferences: Estimation and validation for the case of alternative-fuel. Submitted in February 2014 to *Transportation Research Part A*.

DTU Transport, Kgs. Lyngby, 2014

Anders Fjendbo Jensen

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At DTU Transport, I would especially like to thank my supervisors, Associate Professor, Elisabetta Cherchi and Associate Professor, Stefan Lindhard Mabit, for being extremely accessible and supportive throughout the entire PhD. Thank you for all your help and inspiration. I would also like to thank Senior Researcher, Linda Christensen, for including me in electric vehicle projects during my master thesis and for her input in the initial phase. Last, but not least I would like to thank my wonderful colleagues and fellow PhD students who create a rich and pleasant research environment.

From September to December 2011 I visited Pontificia Universidad Católica de Chile. It was a rewarding stay and it helped me to improve specific parts of the thesis. A special thanks to Professor Juan de Dios Ortúzar for providing this opportunity and for his generous input and fruitful discussions throughout the stay and for the rest of the thesis. I would also like to thank Luis Ignacio Rizzi and Julián Arellana who kindly devoted time to discuss my research with me. Furthermore, I am thankful to several students at the department who showed great hospitality during the stay making it extra joyful for me and my girlfriend, Ida. Felipe, Daniel and Julián, let's stay in touch.

A number of individuals and organisations have contributed with input and information and I am pleased to acknowledge Professor Patricia Mokhtarian from University of California at Davis, who kindly devoted time to comment on the attitudinal questions included in the final survey, which greatly improved this part of the thesis. The Danish Electric Vehicle Alliance kindly helped me with information about the Danish electric vehicle market, the Norwegian Information Committee for Road Traffic (OFV) was helpful with supplying data from Norway and Netherlands Enterprise Agency (RVO) kindly provided data from the Netherlands.

Finally, I would like to thank my family and friends for their support throughout the years.

SUMMARY

Over the last decades, several studies have focused on understanding what drives the demand for electric vehicles (EVs). However, EVs still face large difficulties in developing into a mass market product. It is now recognised that individuals make choices based on a mixture of strategies that involve trade-offs between current characteristics of the alternatives (as in typical neoclassical economic theory) and several effects of bounded rationality. In this connection, some studies have shown that in addition to the objective characteristics of the vehicles, individuals' attitudes toward the environment have an impact on the choice of EVs. However, all these studies assume that individuals have pre-defined preferences. EVs are emerging products that few people have experienced and preferences and attitudes might change as the market for new products expands and individuals acquire real-life experience with the new technology and better understand how it affects their lives.

The objective of this thesis is to investigate the extent to which direct experience with an EV affects individual preferences for specific EV characteristics and attitudes towards relevant topics and how this impacts market elasticity and the diffusion of the EV into the car market. In particular the thesis (1) proposes a methodology to collect adequate data on choices before and after respondents obtain real-life experience with EVs; (2) uses advanced hybrid choice models estimated jointly on the before and the after data to model changes in preferences and attitudes as a results of the real-life experience and (3) tests a method to improve the forecasts of the demand for EVs by combining the disaggregate choice model with a diffusion model, taking into account the time dependent adoption process.

The methodology used to collect the data consists of a long panel survey where individuals are interviewed before (wave 1) and after (wave 2) they have had real-life experience with an EV for the duration of three months in a demonstration project. Considering the very small share of actual EV owners, Stated choices (SC) were used to elicit potential consumer's preferences. The survey includes (*i*) information about current vehicle stock and plans for future purchase; (*ii*) a SC experiment between an EV and a conventional internal combustion engine vehicle (ICV); (*iii*) background information about the respondent and family, and (*iv*) a number of statements to measure the attitudes of *environmental concern*, *appreciation of car features*, *interest in technology*, *general opinions towards EVs* and *scepticism*. The same survey was then repeated in wave 2. First, a SC experiment was built with orthogonal design and tested with a sample of 369 individuals. The experience obtained from this data collection and prior estimates was then used to build the final survey with a SC experiment based on efficient design. The two datasets are very similar, with a few differences in some SC attributes and the inclusion of the no-choice alternative only in the SC experiment of the final survey. In both surveys the scenarios presented in the experiment are customized based on a relevant car purchase as indicated by each respondent.

An in-depth descriptive analysis of the data clearly indicates that preferences for several attributes changed between the two waves. In general the EV is chosen fewer times in wave 2 than in wave 1. In both waves, the EV is chosen more often if the car purchase used as reference is not the only car in the family or if it is a small car. Analyses of the answers to the attitude statements indicate that respondents only change attitude if the statements are EV related. For example, with real-life experience, respondents indicate a more positive view on the driving performance of EVs and this change is significantly higher for women than for men. Furthermore, respondents indicate less concern about having to charge the EV. On the other hand, they indicate a higher concern for being able to maintain their current mobility if they use an EV.

Several hybrid discrete choice models were estimated, using jointly the data from wave 1 and wave 2. The joint estimation allows us to compare individual preferences and attitudes between the two waves directly, after controlling for scale differences between the two datasets. A detailed factorial analysis was first

performed to define the latent variables and the relevant indicators. Several discrete choice models and latent variable models were first estimated separately to identify the best utility specification. Then joint hybrid choice models were estimated to investigate whether real-life experience with an EV changes individual preferences for specific attributes, attitudes toward several topics and the effect that these changes have on the choice. We investigated these effects using the data collected with the orthogonal design and the data collected with the efficient design. With slight differences, results were confirmed with both datasets.

Estimation of the joint hybrid choice model shows that preferences for several attributes indeed do change with real-life experience. Especially, the preference for driving range, which is a critical attribute for EVs, changes and becomes twice as important in wave 2 as compared to wave 1. As in previous studies, results show that environmental concern has a positive effect on the choice of EVs, but results indicate that this effect does not change with real-life experience. Using the dataset collected in the final survey (i.e. with the efficient design), the PhD thesis explores more in detail different sources of individual preference variation and to what extent preferences change as a result of real-life experience with an EV. In particular the thesis investigates (1) the effect of the scale coefficient parameterisation; (2) the effect of respondents' knowledge about being selected; (3) the effect of the latent variable, scepticism and (4) differences in the results obtained with orthogonal and efficient design. We did not find any effect of the scale coefficient parameterisation, but results show that there are differences in preferences if individuals know that they have been selected. Finally, the results indicate that being sceptic reduces the preference for EVs as compared to ICVs, but we only found this effect for individuals without EV experience.

The last part of the thesis discusses the prediction of market share of new products. As most studies for new technologies rely on stated preference data, prediction with choice models requires at least recalibrating the alternative specific constants (ASCs) and the scale to reflect that the unobserved factors in the design year can be different than in the base situation. However, this method gives a quite restrictive calibration of the ASC's, as the current market share for EVs is low. This means that the models become unresponsive, even to major improvements of the EV alternative. The results indicate that some time-dependent factors are not taken into account in the choice models. The effect of diffusion is a time-dependent factor crucial in the case of new products that often need time to obtain a significant market share. The thesis presents and applies an integrated choice and diffusion model to forecast future scenarios of the EV market. Results show that accounting for the diffusion effect allows us to predict a low market share in the initial years and a rapid increase in the market share as diffusion takes effect.

DANSK RESUMÉ

I løbet af de sidste årtier har adskillige undersøgelser fokuseret på at klarlægge præmisserne for efterspørgslen efter elbiler. Det har dog vist sig at være yderst problematisk for elbiler at opnå et egentligt gennembrud på bilmarkedet. Det er nu anerkendt, at forbrugerne træffer deres valg ud fra en blanding af forskellige strategier, som involverer både en direkte vurdering af de forskellige alternativers karakteristika (som i konventionel neoklassisk økonomisk teori) samt adskillige effekter af begrænset rationalitet. Nogle studier har i den forbindelse vist, at foruden elbilers objektive karakteristika har enkeltpersoners holdning til miljøhensyn indvirkning på valget af elbiler. Alle disse studier antager imidlertid, at forbrugerne har foruddefinerede præferencer. Elbilen er et nyt produkt, som kun få forbrugere har brugt i virkeligheden, og deres præferencer og holdninger vil måske ændre sig i forbindelse med, at markedet udvikler sig og forbrugerne opnår erfaring med denne nye teknologi og derved opnår en bedre forståelse for, hvordan den vil kunne påvirke deres hverdag.

Formået med denne ph.d.-afhandling er at undersøge i hvilket omfang, hverdagserfaring med en elbil påvirker brugernes præferencer for specifikke elbilskarakteristika samt holdninger til relevante emner, og hvorledes disse præferencer og holdninger påvirker markedet for elbiler samt den generelle udbredelse af elbiler over tid. Afhandlingen vil navnligt (1) foreslå en metode til at indsamle de nødvendige data vedrørende valg af elbil både før og efter, at respondenterne opnår erfaring med elbiler; (2) benytte avancerede hybride valgmodeller, som inddrager både før- og efter-data for at modellere ændringer i præferencer og holdninger som resultat af den egentlige erfaring og (3) teste en metode til at forbedre fremskrivningerne for efterspørgslen efter elbiler ved at kombinere en valgmodel med en diffusionsmodel, hvor der tages hensyn til, at forbrugere behøver tid, før de accepterer og derved overvejer at købe et nyt produkt på markedet.

Metoden, som er brugt til at indsamle data, består af en longitudinel undersøgelse, hvor enkelpersoner er interviewet både før (runde 1) og efter (runde 2) de har opnået erfaring med en elbil i en periode på 3 måneder ved at deltage i et demonstrationsprojekt. I betragtning af den lave markedsandel for elbiler benyttes respondenternes erklærede valg i en række hypotetiske valgsituationer (stated choices, SC) for at indhente forbrugernes præferencer. Undersøgelsen inkluderer (i) information om den nuværende bestand af biler i husstanden og planer om fremtidige bilkøb; (ii) et SC-eksperiment mellem elbil og en konventionel bil med forbrændingsmotor; (iii) baggrundsinformation om respondenten og respondentens husstand og (iv) en række udsagn, der benyttes til at måle *holdningen til miljø, interesse for biler, interesse for teknologi, generel holdning til elbiler* samt *en generel skeptisk holdning.* Den samme undersøgelse er gentaget i runde 2. Først blev et SC-eksperiment udviklet med ortogonalt design og testet på 369 respondenter. Erfaringerne fra denne dataindsamling samt de estimerede parametre fra en valgmodel, estimeret på disse data, blev så benyttet til at opbygge den endelige undersøgelse med et SC-eksperiment baseret på et efficient design. De to datasæt er meget lig hinanden – med nogle få forskelle i faktorerne i SC-eksperimentet, samt at muligheden for ikke at vælge nogle alternativer kun var inkluderet i den endelige undersøgelse. I begge undersøgelser er valgsituationerne i SC-eksperimentet tilpasset til et relevant bilkøb hos hver enkelt respondent.

Den beskrivende analyse af de indsamlede data indikerer klart, at præferencerne for adskillige egenskaber ændrer sig mellem de to runder. Generelt er elbilen valgt færre gange i runde 2 end i runde 1. I begge runder er elbilen valgt oftere, hvis bilkøbet, brugt som reference, ikke er den eneste bil i husstanden, eller hvis der ønskes en lille bil. Analysen af svarerne på de inkluderede holdningsudsagn indikerer, at respondenterne kun skifter holdning, hvis udsagnet er elbilsrelateret. F.eks. indikerer respondenter med elbils erfaring et mere positivt syn på elbilers køreegenskaber, og denne ændring er signifikant større for kvinder end for mænd. I runde 2 indikerer respondenterne ydermere, at de bekymrer sig mindre om at skulle oplade elbilen

sammenlignet med runde 1. På den anden side indikerer respondenterne dog større bekymring for, om de kan bibeholde deres nuværende mobilitet ved brug af en elbil.

Adskillige hybride diskrete valgmodeller er estimeret baseret på data fra både runde 1 og runde 2 i samme model. På denne måde er det muligt at sammenligne individuelle præferencer og holdninger mellem de to runder direkte, efter at der er tage højde for eventuelle skalaforskelle mellem de to datasæt. Der er udført en detaljeret faktoranalyse for at definere de latente variable og de relevante indikatorer. Adskillige diskrete valgmodeller og modeller for de latente variable er først estimeret separat for at identificere den bedste nyttefunktion. Herefter er de hybride valgmodeller estimeret for at undersøge, om det at have direkte erfaring med en elbil har forandret individuelle præferencer for de enkelte alternativers karakteristika og holdninger til de forskellige emner samt den virkning, disse forandringer har på selve valget. Disse effekter blev både testet med data indsamlet vha. det ortogonale design og med data indsamlet med det efficiente design, hvilket tillader validering af resultaterne. Bortset fra nogle mindre forskelle er resultaterne bekræftet i begge datasæt.

Estimeringen af de hybride valgmodeller viser, at præferencerne for adskillige egenskaber ændres som en konsekvens af den opnåede erfaring. Særligt ændres præferencen for elbilens rækkevidde, hvilket er en kritisk egenskab for elbiler. Sammenlignet med runde 1 er effekten af denne egenskab fordoblet i runde 2. Som også vist i tidligere studier indikerer resultaterne, at positive holdninger til miljø har en positiv effekt på valg af elbil, men resultaterne viser, at denne effekt ikke ændres med mere erfaring med elbiler. Baseret på beregninger med data fra den endelige undersøgelse (dvs. med det efficiente design) undersøger afhandlingen flere årsager til variationen i de individuelle præferencer, og i hvor høj grad præferencer ændres med erfaring med elbiler. Således undersøger afhandlingen (1) effekten af at parametrisere skalaeffekten; (2) om det, at respondenterne ved, at de er udvalgt til at deltage i demonstrationsprojektet, har en effekt; (3) effekten af den latente variabel for at være særligt skeptisk og (4) forskelle mellem resultaterne opnået med det ortogonale design og det efficiente design. Resultaterne viser, at der er forskelle i præferencer, hvis respondenterne ved, at de er udvalgt til at deltage i demonstrationsprojektet. Beregningerne blev imidlertid ikke forbedret ved at parametrisere skalaeffekten. Endelig viser resultaterne, at en særlig skeptisk holdning reducerer præferencerne for elbiler sammenlignet med konventionelle biler, men at denne effekt er kun gældende for personer uden erfaring med elbiler.

Den sidste del af undersøgelsen diskuterer problematikken med at fremskrive markedsandelen for nye produkter på markedet. Idet de fleste studier vedrørende nye produkter beror på erklærede præferencer i hypotetiske situationer (stated preferences, SP), vil fremskrivninger med valgmodeller som minimum nødvendiggøre, at de alternativ-specifikke konstanter samt skalaen rekalibreres for at tage højde for, at effekterne, der fanges af fejlleddet, kan være forskellige mellem basisåret og året, der fremskrives til. Denne metode giver imidlertid anledning til en meget restriktiv kalibrering af de alternativ-specifikke konstanter, idet den nuværende markedsandel er meget lille. Det betyder, at de estimerede modeller ikke påvirkes, selv med markante forbedringer af elbilens egenskaber. Dette resultat indikerer, at der også findes nogle tidsbestemte effekter, som ikke er taget i betragtning i valgmodellen. Diffusioneffekten er en tidsafhængig effekt, som er essentiel for nye produkter, der ofte kræver tid, før de opnår en egentlig markedsandel. Denne ph.d.-afhandling præsenterer og anvender en integreret valgmodel og diffusionsmodel til at fremskrive scenarier for markedet for elbiler. Resultaterne viser, at når diffusionseffekten medtages, er det muligt at fremskrive scenarier, hvor der opnås en begrænset markedsandel i de indledende år, hvorefter der opnås en markant stigning i markedsandelen, så snart diffusionseffekten træder i kraft.

CONTENTS

1 INTRODUCTION

The increasing focus on global warming, air pollution and dependence on fossil fuels has led to a greater interest in new technologies for personal transport. Consequently, more and more car manufacturers are introducing Electric Vehicles[1] (EVs) and the availability of EV models is greatly increasing these years.[2] In addition, compared to many failed attempts at market introduction over the past decades, the performance and durability have improved so that EVs are now much more competitive with conventional vehicles EVs in the early 1990s[3]. On the demand side, however, the EV continues to face extreme difficulties obtaining a significant market share. The popularity differs quite a bit from country to country. The largest EV market is found in USA, where 46,000 new units were registered in 2013[4]. However, looking at the share of new car sales, this ranks USA 5th worldwide, while Norway by far obtains the leading position[5]. In 2013, almost 6% of all new car registrations in Norway were EVs and looking only at November and December, the share goes beyond 11%[6]. In comparison, only 0.3% of new car registrations in Denmark in 2013 were EVs[7].

In the absence of enough owners to measure revealed data from, stated preferences (SP) methods are the most established way to elicit preferences for alternative fuel cars[8] (AFVs) and their characteristics from potential consumers. However, although carefully customized, well designed and conducted, SP experiments are hypothetical settings and hence do not represent actual demand. For forecasting, however, information about revealed demand is crucial to reproduce the aggregate baselines and to re-estimate the model for the future years. Consequently, many studies using SP data only present model estimations and/or trade-offs between coefficients and do not provide forecasts (e.g. Ito et al. 2013; Hidrue et al. 2011; Potoglou & Kanaroglou 2007; Ramjerdi & Rand 2000; Beggs et al. 1981). Some studies use the estimated coefficients to calculate and compare AFV market shares in specific scenarios (e.g. Glerum et al. forthcoming; Mabit & Fosgerau 2011; Dagsvik et al. 2002; Ewing & Sarigöllü 2000; Bunch et al. 1993; Calfee 1985), but do not claim that they are actual forecasts of the market. A few studies, (Knockaert 2005; Adler et al. 2003) present models estimated on SP data which are intended for larger simulations systems, but do not report how these models would be integrated. Brownstone et al. (2000) estimate models jointly on data from revealed and stated preferences in order to improve the estimation. They find that the joint estimation gives a much lower EV market share (18% instead of 42%) than when using only SP data. Batley et al. (2004) use SP data collected in the United Kingdom and re-calibrate the ASC using the USA market shares found in Brownstone et al. (2000). Using results from other countries to re-estimate the ASC may be a reasonable solution in the absence of better information. However, results are sensitive to the reference market share used to re-calibrate the ASC, so care must be taken with respect to the type of market considered as reference and its characteristics.

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[1] Many new vehicle technologies use electric motors together with different types of propulsion (i.e. hydrogen, gasoline/battery hybrid). In this study we focus on pure battery electric propelled vehicles.

[2] Based on information from www.delk.dk (homepage of Danish EV committee) and the report from Danish EV Alliance “From plan to action”, November 2013. By the end of 2013, around 10 different EV models were available in Denmark compared to only 5 models in mid 2012.

[3] The first highway capable EVs with room for more than 2 persons entered the Danish market in 2010, see i.e. www.delk.dk

[4] According to http://evobsession.com/electric-car-sales-increased-228-88-2013/

[5] According to http://www.hybridcars.com/top-6-plug-in-car-adopting-countries/2/

[6] According to data from Opplysningsrådet for Veitrafikken AS (Norwegian Information Comittee for Road Traffic)

[7] According to data from The Danish Car Importers Association.

[8] Alternative fuel cars cover many technologies such as biofuel, hydrogen fuel cell but also electric vehicles. This thesis only focuses on electric vehicles.

Another challenge when studying the market for new products is the time-dependent diffusion process, defined as the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers 2010). Within the marketing literature, several diffusion models have been developed to forecast sales, penetration or adoption of durable goods, novelty items and new technological developments (Tellis & Chandrasekaran 2012; Mahajan 1986). However, most of the diffusion models are single product models, which do not take competition with other variants or categories into account. A couple of studies have tried to integrate the diffusion models and choice models (see e.g. Jun & Kim 2011; Weerahandi & Dalal 1992), but they used very simple demand models and mostly at an aggregate level. So far the diffusion has not been applied to emerging car technologies. One reason for this could be that revealed market shares for several time periods are needed to estimate the parameters of both the diffusion and choice models and such information has been sparse. As data become more available, there is an opportunity to explore how diffusion models and choice models can be used to improve the understanding of the potential market potential of emerging car technologies.

An important issue when using SP experiments to study new products is that individuals express their preferences without having any real-life experience with the product they are faced with. With new technologies there might be misconceptions about the impact that certain characteristics of the new product can have on the individual's daily life. Kurani et al. (1996) expressed scepticism about SP methods used for EV analyses, suggesting that it is not possible for consumers to have preferences for attributes such as limited driving range, home charging, zero tail pipe emissions and other unique attributes of EVs, because they have not experienced them and therefore have not been able to construct adequate preferences. The literature from the field of psychology suggests that preferences and attitudes might change with the experience individuals get from using or consuming a certain product (Thøgersen & Møller 2008). This is even more likely to occur when the product is new, since there might be a misconception about the impact that the new characteristics of the alternative can have on the individual's life (for example the smaller driving range of EVs compared to that of conventional cars). For the EV alternative, therefore, it is important to study if and how preferences for different characteristics of the product change as customers obtain more information or experience. People construct their preferences when encountering a new domain (such as when new products enter the market or some existing products are completely revamped) as they are forced to rethink their choice. Hence SP studies are well suited to measure formation of preferences. Demonstration projects have previously been used to give consumers real-life experience with EVs. Based on questions about attitudes and purchase willingness for only eight families, who participated in a demonstration project over three months, Gärling and Johansson (1998) measured a "somewhat" reduced willingness to purchase an EV as families obtain more experience with the vehicles. The reasons given in the last interview for not being willing to purchase an EV were: too short driving range, too long recharging time, too small vehicles, too high purchase price and uncertainty with service, safety and future battery costs. More recently a demonstration project in Berlin (Franke et al. 2012; Franke & Krems 2013) studied a sample of 79 participants who also had an EV available for three months, and found that before the trail 64% indicated positive purchase intentions, while this number decreased to 51% after the trial. On the other hand, the minimum acceptable driving range that the individuals would accept from an EV was statistical significantly reduced from 145 km before the trial to 136 km after the trial. Both these studies refer to respondents' absolute indications of characteristics of the EV and it was therefore not possible to measure the marginal valuation and compare the importance of different attributes. Instead, SP data collected at different stages in the demonstration projects would allow for explicit choice modelling of the preferences and the effect they have on the market.

Recent studies have shown that besides objective characteristics, variables, such as attitudes and perceptions that are not directly observable, can affect individual behaviour. For example, environmental concern has been found to have a positive effect on environmental friendly alternatives in several studies (see e.g. Atasoy et al. 2013; Daziano & Bolduc 2013; Vredin Johansson et al. 2006). Furthermore, specific attitudes towards the car alternative have been found to have an effect in mode choice studies (Atasoy et al. 2013; Abou-Zeid et al. 2010). Due to several failed attempts of market introduction during the 1980's and the 1990's, there might be a more negative attitude towards EVs than the today's product quality justifies, which should be studied further. A few papers, (e.g. Daziano & Bolduc 2013; Glerum et al. forthcoming) have studied attitudes specifically in the choice of new car technologies, but there is no evidence on how direct experience with an EV affects individual preferences and attitudes.

The main objective of this thesis project is to investigate if and how preferences and attitude changes with real-life experience with EVs and to what extent such changes affect the EV market. Given the main objective, this thesis aims to contribute within three specific areas: Data collection, Choice modelling and Forecasting.

The following chapters are intended to present the background theory used to develop the thesis. Therefore, the following chapters do not deal with the details of the methodologies and results as these are presented in the papers. In particular, Chapter 2 introduces the general problems with data collection. It discusses revealed preference and stated preference data, different ways of building choice experiments with experimental design and potentials of using panel data. The details of the methodology used to collect data before and after individuals have tried an EV in real life and the results from the survey are then presented in Paper 1. Chapter 3 presents a general overview of the theory underpinning discrete choice models. In particular, it discusses modelling with panel data (the mixed logit model), with data from different sources and integrating the latent variables into the discrete choice framework (the hybrid choice model). The problems of the stability of individual preferences, due to real-life experience with an EV and the hybrid choice model jointly estimated with data collected before and after real-life experience, are presented in Paper 2. The model in this paper is estimated using the first set of data collected using an orthogonal design and accounts for the effect of the latent pro-environment attitude. A working paper (Paper 3) then reports the results for the joint hybrid choice models estimated using the data collected with an efficient design. In particular it discusses (1) the effect of the scale coefficient parameterisation; (2) the effect of respondents' knowledge about being selected; (3) the effect of the latent variable, scepticism and (4) a comparison between orthogonal and efficient designs. Chapter 4 discusses the general problem of forecasting demand. It introduces the theory behind diffusion models and discusses the need and the problems of combining choice models and diffusion models. The details of the methodology set up and an application on real data are discussed in detail in Paper 4. Chapter 5 summarises the main results of the thesis and finally, conclusions and further perspectives are presented in Chapter 6.

2 DATA COLLECTION

Obtaining useful data about a product to be investigated can be challenging regardless of whether the product is well established or emerging in the market. Revealed Preference (RP) data reflect actual behaviour which is indeed a great advantage. However, this type of data is often very expensive to collect and the data is limited to existing choice situations and attributes. Even for existing choice situations, some factors can be extremely difficult to measure and there may be insufficient variation in certain key factors to allow estimation with RP data (Louviere et al. 2000). With Stated Preference (SP) data, the researcher can define the alternatives, the attributes and how the levels of the attributes vary. In this way, a well-designed experiment can provide good estimates of consumer's trade-offs for factors that are difficult to measure or do not exist, or for factors where it is difficult to measure enough variability. Furthermore, with SP data, multiple observations can easily be obtained from each respondent by presenting several scenarios during the interview.

Obviously, there are limitations related to such hypothetical data. The consumer is not exposed to the same constraints as in real life and they might not be willing to say what they would actually do, they might be biased towards what they think the interviewer expects or they might even not know what they would do if the hypothetical situation was real. While this is an unavoidable weakness of SP data, respondent participation can be enhanced in several ways which include: focusing on a specific occasion rather than a general one, using a realistic choice context (i.e. by customizing the choice scenarios to each individual), ensuring that all relevant attributes (with realistic attribute levels) are included without making the experiment too complex and by allowing the respondents to opt out if none of the presented alternatives are attractive (Ortúzar & Willumsen 2011). Furthermore, the respondent should be prepared - as much as possible - for the choice tasks before the scenarios are presented, i.e. by providing necessary information about some alternatives or attributes. Today, SP methods are considered an important tool within the field of transport modelling, especially when studying completely new alternatives.

In the data collection conducted for this thesis, it was decided to use SP data for two reasons: (1) the EV alternative is still in the emerging phase and it is difficult to measure preferences from real market data and (2) we were interested in the effect of real-life experience on these preferences. If there are still too few EV purchasers in the real market *without* EV experience, there are certainly not enough EV purchasers in the real market *with* experience. As always with SP methods, extensive efforts were needed to determine the relevant alternatives, attributes and attribute values. The overview in Table 1 shows the attributes included in 17 SP studies on alternative fuel vehicles (AFVs) conducted within the last twenty years. All of them include purchase price and most of them include fuel costs (in different ways). Furthermore, it is common to include a driving performance attribute (e.g. represented by acceleration or top speed) and environmental performance, which is represented by carbon emissions or other tailpipe emissions. Fuel availability is also an important attribute, but as many of the studies considered several different AFVs (of which the EV alternative is not always included), the charging options for EVs have almost never been considered. Recently (after the experiment in this thesis was developed), a few studies have added some interesting attributes in the EV context. Bočkarjova et al. (2013) included the detour and waiting time to reach a charging point. In addition, they included the possibility of attaching a tow hitch (which is common in many European countries, including Denmark), as this issue became evident in their pilot. Ito et al. (2013) provide a more detailed description of charging options compared to earlier studies as they included refuelling (charging) time and then combined refuel availability and refuel location in one attribute.

Table 1: Overview of attributes used in previous SP experiments with AFVs[9]

	Attributes	Glerum et al. (forthcoming)	Ito et al. (2013)	Bočkarjova et al. (2013)	Mabit & Fosgerau (2011)	Hidrue. et al. (2011)	Jensen (2010)	Bolduc et. al. (2008)	Achtnicht (2008)	Potoglou & Kanaroglou (2007)	Horne et. al. (2005)	Batley et. al. (2004)	Adler et. al. (2003)	Dagsvik et. al. (2002)	Hensher & Greene (2001)	Train & Brownstone (2000)	Ewing and Sarigöllü (1998)	Bunch et. al. (1993)
Monetary	Purchase price	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	Expected resale price			x														
	Registration fee														x			
	Fuel costs	x	x	x		x	x	x	x	x	x	x	x		x			x
	Fuel costs in 5 years			x														
	Refuel costs at home															x		
	Refuel costs at stations															x		
	Fuel consumption													x				
	Maintenance costs	x								x			x				x	
	Battery lease	x																
	Fuel and parking costs																x	
	Fuel and maintenance costs				x													
Vehicle characteristics	Acceleration				x	x				x			x		x	x	x	x
	Top speed						x					x		x		x		
	Driving range		x	x	x	x	x					x		x	x		x	x
	Boot size														x			
	Battery life						x											
	Gradability												x					
	Tow hitch possibility			x														
	Engine power							x	x		x							
Fuel Infrastructure	Fuel availability		x					x	x	x	x	x						x
	Refueling time		x	x		x	x									x	x	
	Refuel location		x				x					x						
	Distance to home charging						x											
	Detour time			x														
	Charging at work						x											
Policy	Incentives	x						x		x	x		x					
	Commuting time (as a result of incentives)																x	
Environmental	Pollution levels, tailpipe emissions					x				x	x	x				x	x	x
	Carbon dioxide emissions		x	x			x	x	x									

[9] On several occasions attributes with the same description in the table were specified differently in each study. We pooled attributes with similar meaning in the table and we did not include attributes for vehicle body type and manufacturer, for simplicity.

Even when the alternatives, the attributes and the attribute values have been defined, there are a number of tasks to consider when generating the experimental design needed to set up the choice experiment. The experimental design is developed to control the variation of the attributes over the attribute levels across the choice situations. Considering all possible combinations of the attribute levels, will quickly become impossible in practice, as the number of attributes increases. Therefore, it is common only to consider a subset of the combinations, while still reducing confounding effects and maintaining often desired properties such as attribute level balance.

A common method is to use orthogonal design, which is generated to satisfy orthogonality, meaning that there are zero correlations between the attributes (Ortúzar & Willumsen 2011). This is particularly convenient for discrete choice models. Recently, it was suggested to choose the attribute level combinations that will result in the smallest possible parameter covariance matrix (Rose & Bliemer 2009). While this method may significantly optimise the choice experiment (e.g. by lowering the number of choice tasks or obtaining the same amount of information from less respondents), it comes at the cost of having to make a number of assumptions about the model to be estimated. If this is not the true structure, potential bias could be introduced. Orthogonal designs are more general, but they are based on regression assumptions which are far from the assumptions used in discrete choice models. Theoretical work (e.g. Bliemer et al. 2005) shows that efficient designs have good properties, but there is still no evidence with real data on the consequences of using efficient design instead of orthogonal design, e.g. if a wrong model specification is used. Another criticism of the use of efficient design is that prior knowledge about the parameters of the model is required in the design generation process. As it is usually not possible to obtain very precise parameter priors, Bayesian efficient designs can be used. They allow the parameters to follow some distribution. In this thesis it was decided to use an efficient design as good prior information would become available from the pilot data collection, which was expected to be quite comprehensive. The pilot experiment was built with an orthogonal array and based on the obtained priors and a Bayesian efficient design was then generated for the final survey. Although the comparison between experimental designs is not an objective of this thesis, having two large data sets of a high quality collected on the same phenomenon with both orthogonal and efficient design, allows for some interesting analyses and comparisons between the two methods.

Although several observations are most often collected for each individual, SP data does not refer to different periods in time. As such they do not allow researchers to investigate temporal effects as in the typical panel data. Panels used to investigate temporal effects can be classified into two categories: long and short panels. Long survey panels consist of repeating the same survey (i.e. with the same methodology and design) at different times, for example once or twice a year for a certain number of years, or before and after an important event. Short survey panels consist of multi-day data where repeated measurements on the same sample of units are gathered over a "continuous" period of time, but the survey is not repeated in subsequent years (Ortúzar & Willumsen 2011). The data collected in this thesis can be considered a panel in two dimensions because: (1) several observations were collected per individual in the SP experiment and (2) the observations are collected at different points of time, before and after the event of real-life experience with the EV.

Studies have shown that psychological effects can affect individual behaviour. Hence attitudinal information on relevant topics is often collected. When designing attitudinal surveys, it is useful to develop a list of conceptual constructs (latent variables) that are found relevant for the study. Then several attitudinal statements are developed for each construct. It is good practice to balance the direction of the statements, e.g. the statements "For me, the car is just a convenient way to travel" vs. "It means a lot to me what signals the car sends to its surroundings". Questions or statements in an attitudinal survey are often the result of considerable work in designing the statements so that they measures what was intended, and also so that they are reliable across segments, i.e. it is possible for everybody in the sample to give an adequate response. For example, how would an individual who never travels by car respond to statements about car travel? One way to deal with this problem would be to include a “don’t know”/“not relevant” option. Obtaining precise information from all participants might often require a “don’t know”/not relevant” option, but this also makes the analysis of the data more difficult, since a numerical value cannot simply be attached to such a response. Furthermore, for statements that require a bit more effort from the respondent, this might be used as an easy way for the respondents to avoid having to make this effort. In the thesis, we tried to avoid statements that would not apply to the entire sample in general.

Attitudinal information can take the form of continuous, binary or categorical responses to a number of statements included in the survey. When the attitudinal data has been collected, a factor analysis can be performed to analyse how the different attitudinal indicators cluster and if they actually represent the latent variables as intended. This should be tested thoroughly using pilot surveys. In this PhD attitudes towards several topics found relevant in the choice of EVs were measured. This work was greatly inspired by previous studies (e.g. Mokhtarian et al. 2001; Atasoy et al. 2010) and also greatly benefitted from fruitful communication with Professor Patricia Mokhtarian at University of California at Davis.

3 MODELLING DISCRETE CHOICES

The theoretical basis used for discrete choice models is mainly Random Utility Maximization (RUM). The general assumption in choice models is that each individual makes a choice based on a rational evaluation of the characteristics of the available alternatives. Each alternative is described by a stochastic utility function to take into account the randomness caused e.g. by unobserved attributes, unobserved taste variations or measurement errors. Hence, the utility from alternative j obtained by an individual n at occasion t is described as:

$$U_{jnt} = f(\beta_{jnt}, x_{jnt}) + \varepsilon_{jnt}, \tag{3.1}$$

Where x_{jnt} is a vector that includes alternatives and individual characteristics; β_{jnt} is a vector of coefficients describing the effect of these variables on the utility as well as alternative specific constants and ε_{jnt} are random terms. The choice probability of alternative i is then defined as the probability that the utility of alternative i is greater than or equal to the utilities of all other alternatives in the choice set C_{nt}:

$$P_{int} = \Pr(U_{int} > U_{jnt}, \forall j \in C_{nt}, j \neq i) \tag{3.2}$$

The simplest form of the discrete choice model is the Multinomial Logit (MNL) model, which is obtained by assuming that the error terms are independently and identically distributed Extreme Value type 1 and that the coefficients are fixed across individuals[10] ($\beta_{jnt} = \beta_{jt}$). This gives the MNL closed form of choice probabilities that are easy to work with (Ortúzar & Willumsen 2011, Chapter 7):

$$P_{int} = \frac{e^{\mu f(\beta'_{it}, x_{int})}}{\sum_j e^{\mu f(\beta'_{jt}, x_{jnt})}}, \tag{3.3}$$

where μ is a positive scale parameter related to the variance of the ε_{jnt}'s. The scale μ cannot be identified and is often for convenience set to be equal 1. However, when comparing the probabilities from separate models, the relative scale between the models should be taken into account. In the following, μ is only included when relevant.

The Mixed Logit model allows the parameters of the utility specification to vary randomly across the population. Hence, the probability function is the integral of the standard MNL probability over all mixing parameters:

$$P_{int} = \int \left(\frac{e^{\beta'_{int} x_{int}}}{\sum_j e^{\beta'_{jnt} x_{jnt}}} \right) f(\beta) d\beta, \tag{3.4}$$

where β can follow any distribution. Without entering into the discussion of the distribution, as this is not the objective of this thesis, it is important to mention that there has been an important discussion in the literature (e.g. Fosgerau & Bierlaire 2007; Meijer & Rouwendal 2006) about the choice of mixing distribution and its effect on the model estimation. However, the most used distribution is still the normal distribution with mean b and covariance W, i.e. $f(\beta|b, W)$, where all elements in b and W need to be estimated except for those constrained for identification purposes.

Mixed Logit models allow researchers to account for the structure of panel data (i.e. data with several observations per individual). Consider T observations gathered from each individual and that the parameters in β are allowed to vary across individuals but otherwise stable. The probability that a person makes this

[10] Differences between individuals are then considered by interactions between attributes and background variables

sequence of choices, $\mathbf{i} = \{i_1 \dots i_T\}$, is the integral of the product of the choice probabilities for each observation over all values of β (Train 2009):

$$P_{in} = \int \prod_{t=1}^{T} \left(\frac{e^{\beta'_{in} x_{int}}}{\sum_j e^{\beta'_{jn} x_{jnt}}} \right) f(\beta) d\beta \tag{3.5}$$

3.1 Modelling Different Preferences Across Datasets

Sometimes it is necessary or beneficial to estimate models on observations from different datasets. This is typically the case when using combined RP/SP datasets in order to improve the quality of data related to some variables, or when we would like to compare variation in preferences across groups of individuals. If there are reasons to believe that different sub-samples (or segments of the population) might show different preferences for specific attributes but not differences in the scale, a dummy variable for specific segments can be used. Otherwise the difference in scale between datasets also needs to be estimated, to be able to compare preferences across datasets directly.

Consider two datasets, B and A[11], where we believe there might be a variation in scale besides the variation in preferences for specific attributes. The model can then be specified as follows:

$$\begin{aligned} U^B_{jnt} &= \gamma'_{jnt} z^B_{jnt} + \beta'^B_{jnt}\, x^B_{jnt} + \upsilon_{jnt} o_{jnt} + \varepsilon^B_{jnt} \\ U^A_{jnt} &= \theta\left(\gamma'_{jnt} z^A_{jnt} + \beta'^A_{jnt}\, x^A_{jnt} + \nu_{jnt} u_{jnt} + \varepsilon^A_{jnt}\right) \end{aligned} \tag{3.6}$$

Where U^B_{jnt} and U^A_{jnt} are the utility associated with the individuals that belong to the two datasets, z^B_{jnt} and z^A_{jnt} are vectors of variables shared across the data sets for which the associated parameters in the vector γ_{jnt} are expected to be equal across the datasets, x^B_{jnt} and x^A_{jnt} are vectors of variables shared across the data sets but the associated parameters (β^B_{jnt} and β^A_{jnt}) are expected to be different across datasets whereas o_{jnt} is a vector if variables only included in data set B and u_{jnt} is a vector of variables only included in data set A. The associated parameters for o_{jnt} nand u_{jnt} are included in the vectors υ_{jnt} and ν_{jnt} , respectively. Providing that at least one coefficient is generic between B and A, the relative variance $\theta = \frac{\mu_B}{\mu_A}$ between the datasets is identifiable and it can be estimated simultaneously with the rest of the parameters. With this specification, the remaining coefficients can be compared directly between the two datasets. A simple t-test for equality between two parameters can then be used to determine whether coefficients are dataset specific or not, and whether individual preferences in the two data sets are significantly different. Note, that if θ is not significantly different from 1, the scale can be considered the same in the two datasets.

Equation 3.6 assumes homogeneity in the scale across individuals. However, this assumption is not always verified and can be tested specifying a parameterisation of the scale parameter θ, for instance:

$$\theta_n = \exp(\tau + \varphi' x_n), \tag{3.7}$$

where τ is a constant, x is a vector of explanatory variables (these are usually background characteristics but can also include latent effects) and φ is a vector of coefficients, explaining the effect on each variable on the scale.

[11] We use this notation to be consistent with the models presented in Paper 2.

3.2 MODELLING PREFERENCES AND ATTITUDES

The hybrid choice model is the framework most often used to integrate discrete choice models and latent variable models, explicitly allowing for the latent variable to be included as an explanatory variable in the discrete choice model. The framework was originally proposed by Ben-Akiva et al. (1999) and generalized by Walker (2001).

The latent variable x_n^* can be linked to observable variables (e.g. characteristics of the individual) x_n with the following specification in the *structural* equation:

$$x_n^* = \lambda' x_n + \omega_n, \tag{3.8}$$

where λ is a vector of coefficients associated with the observable variables and ω_n is a normal distributed error term with zero mean and standard error σ_ω. Since the latent variable cannot be measured, the effect that it has on measurable indicators (e.g. responses to attitudinal statements) is measured and included in the system of *measurement* equations:

$$I_{rn} = \gamma_r + \alpha_r x_n^* + \upsilon_{rn}, \tag{3.9}$$

where I_{rn} is one of $r = 1 \ldots R$ indicators for the latent variable, γ_r is the intersect, α_r is the coefficient associated with the latent variable and υ_{rn} is a normal distributed error term with zero mean and standard error σ_υ. Usually γ_1 and α_1 are normalized to zero and one for identification purposes.

Since the latent variable x_n^* enters the utility specification of the discrete choice model, the unconditional probability is then the integral over the distribution of ω:

$$P_{jn} = \int_\omega P_{jn}(\omega) f_{x^*}(\omega) \prod_{r=1}^{R} f_{Ir}\big(I_{rn} | \mathrm{x}_\mathrm{n}^*(\omega)\big) d\omega \,, \tag{3.10}$$

where the distributions of the latent variable and the indicators, due to the assumptions about the error terms, are respectively:

$$f_{x^*}(\omega) = f_{x^*}(x_n^* | x_n; \lambda, \sigma_\omega) = \frac{1}{\sigma_\omega} \phi \left(\frac{x_n^* - \lambda' x_n}{\sigma_\omega} \right) \tag{3.11}$$

$$f_{Ir}(I_{rn} | x_n^*; \alpha, \gamma, \sigma_\upsilon) = \frac{1}{\sigma_{\upsilon_r}} \phi \left(\frac{I_{rn} - \gamma_r - \alpha_r x_n^*}{\sigma_{\upsilon_r}} \right) \qquad \forall r = 1 \ldots R \tag{3.12}$$

Now, if we consider both the product of the sequence of choice tasks and the product over distributions for each indicator for the attitudinal statements, the unconditional probability is then calculated as:

$$P_{jn} = \int_{\beta,\omega} \prod_t P_{jnt}(\beta_{jn}, \omega_n) f_{x^*}(\omega_n) \prod_r f_{Ir}\big(I_{rn} | x_n^*(\omega_n)\big) f(\beta) f(\omega) d\beta d\omega \tag{3.13}$$

In many model applications, the latent variable is added to the utility specification, as it is expected to affect the overall utility of an alternative. Hence, one or several latent variables could simply be included in the vector of explanatory variables in equation 3.5. However, some latent effects can also affect the marginal preference for some attributes or, as discussed in the previous section, they can affect the scale among datasets. Equation 3-13 is general and holds no matter how the variable affects the preferences in the discrete choice model. It holds also in the case of multiple datasets.

3.3 ESTIMATION

Most studies use the maximum likelihood method for discrete choice model estimation. The goal of this procedure is to identify the parameter values such that the product of the probabilities that the model reproduces for the observed choices is the highest possible (Train 2009). Let P_{jn} be the probability of the observed outcome for individual n and N the sample size. For models, where an exact calculation of the probabilities is possible (such as the MNL model), algorithms can be applied to maximize the log-likelihood (LL) function, which takes the form:

$$LL = \sum_{n=1}^{N} \ln P_{in} \tag{3.14}$$

The greater flexibility of the Mixed Logit model has the drawback of a probability function without a closed form. Hence, exact calculation of the probabilities is not possible. The most common approach, especially when there are more than one mixed parameter is the Maximum Simulated Likelihood (MSL) estimation, where simulation is applied to maximise the objective function:

$$SLL = \sum_{n=1}^{N} \ln(\check{P}_{in}), \tag{3.15}$$

where $\check{P}$ is the approximate choice probability. In outline, the process is as follows: a draw from the specified distribution of β is taken and the MNL probability is calculated. This process is repeated many times and the average across draws of the resulting probabilities is taken as the approximate choice probability (Train 2009). For a panel specification, the product of the probabilities for each individual is calculated in each draw. A high number of draws is needed to reach a good approximation, which substantially increases the calculation time.

4 FORECASTING DEMAND

Within transport planning, models are used to examine the demand sensitivity with respect to changes in important variables and to deliver forecasts of the demand for specific scenarios. Forecasts usually represent the behaviour of an entire population or a market segment. Disaggregate choice models are popular in forecasting as they can account for detailed information about specific characteristics of the different alternatives and characteristics of the consumers when they are used to simulate a scenario. Consider a MNL model estimated on a sample considered representative of the population. A full set of alternative-specific constants $\hat{\alpha}_j$ ensures that the predicted market shares of each alternative j are equal to the observed market shares in the estimation sample MS_j (Ortúzar & Willumsen 2011), hence:

$$MS_i = \frac{1}{N}\sum_{n=1}^{N}\hat{P}_i = \frac{1}{N}\sum_{n=1}^{N}\frac{e^{\hat{\alpha}_j+\hat{\mu}\cdot\hat{\beta}'x_{in}}}{\sum_j e^{\hat{\alpha}_j+\hat{\mu}\cdot\hat{\beta}'x_{jn}}} \tag{4.1}$$

If the sample is non-random, there are different methods to weigh it according to the population. If the model is linear, average values of the explanatory variables may simply be used, as they will give a correct aggregate market share. However, as this is not our case, sample enumeration (Ben-Akiva & Lerman 1985) is an appropriate approach to be used.

If the choice context of the estimated parameters differs from the choice context where the model will be used to make a forecast scenario, then it is often necessary to adjust the constants and the scale to reflect the fact that the unobserved factors may be different between the contexts. The adjusted model can then be used to simulate changes in demand as a consequence of changes in the explanatory variables. When some base scenario market share MS_j and average values for explanatory variables x_j are known, then the constants and the scale of the aggregate model can be re-calibrated with maximum likelihood maximisation or nonlinear regression. Clearly, if a model is estimated solely on SP data (such as most studies on the EV market), then the model cannot be expected to represent a real-life context and should be adjusted before a forecast is conducted. However, as SP data are usually used for new products that do not yet have an established market, it is often not possible (or at least very difficult) to find a revealed market that can be used to adjust the constants and scale; in fact, there is no established way how to calibrate such models to a real-life context. Furthermore, the estimated parameters associated with the explanatory variables might not represent preferences in future scenarios. The sampled individuals from which the preferences were elicited, might have very little knowledge about the products they were presented with. While the demand curve (and hence the preferences of the sample) are usually assumed to be constant in the forecasting scenarios, the elicited preferences might not be representative of future scenarios where the population has better knowledge about the product.

Even though there are a large number of SP studies on EVs, very few of the estimated models have been used to make forecasts. If a market share is calculated, it is usually much higher than what is actually revealed in the respective country (i.e. a market share of 27% was obtained for Switzerland in Glerum et al. (forthcoming) and 18% for the UK in Batley et al. (2004)). In comparison, the country where the EV has experienced the highest actual penetration, Norway, had an EV market share of new car registrations of 5,5% in 2013, whereas it was only 0.03% in Denmark. The predicted market shares are of course highly dependent on the assumptions made for the forecasting scenarios, but they also strongly depend on the assumptions made when re-calibrating the base model. A simple calibration of the constants and scale would generate forecasts that are extremely restrictive or pessimistic in the short term, but they might be correct in the long term. The current low market shares in the real market suggest that there are factors not included in the demand models that should be considered.

On the other hand, it is widely acknowledged, within marketing, that new products or innovations usually need time to gain a sufficient share of the market. Such factors are usually not included in the demand models described above. Within marketing there is a vast literature on quantitative diffusion models representing the market penetration of a new product, process or technology. The term *diffusion* has been defined as the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers 2010). Historical evidence for several product categories introduced in the market shows that such time-depend factors are important (Lilien et al., 2000) and should be considered when forecasting. The best known approach in the marketing literature is the Bass (1969) diffusion model. The theory applies to the timing of adoption and considers two classes of adopters; innovators and imitators. In the basic model, the number of new adopters during time period *t* is described as:

$$a_t = (M_t - Y_{t-1})\left(p + q\frac{Y_{t-1}}{M_t}\right), \tag{4.2}$$

where M_t is the number of eventual adopters, Y_{t-1} is the cumulative number of adoptions occurred before period *t* whereas p and q are coefficients of innovation and imitation, respectively. These coefficients indicate the influence of these classes of adopters on the general adoption process and need to be estimated. Furthermore, M_t needs to be estimated too, but unfortunately it is often necessary to do this separately and include it as exogenous information.

Although several variants have been suggested, diffusion models in their basic form represent the process of diffusion in a single-product framework and do not take into account inter-relationships among various products (Peterson & Mahajan, 1978). This is exactly what disaggregate choice models do, and hence a couple of approaches have been suggested that take diffusion into account and at the same time model the choice between several products or product categories with discrete choice models.

Jun and Park (1999) incorporated diffusion effects and substitution effects in an integrated model. Their motivation is to capture simultaneously the diffusion and substitution processes for *j* successive generations of a durable technology. More specifically, they included the diffusion effect directly into the utility. Consider the following utility expression for alternative j at the time period t:

$$V_{jt} = q_j\big(t - \tau_j + 1\big) + \beta' x_{jt}, \tag{4.3}$$

where q_j is a parameter related to the time dependent diffusion effect for each product and τ_j is the year when the product was introduced into the market. Assuming identically and independently distributed Extreme Value type 1 error terms, the number of sales in each period *t* can be computed as:

$$S_{it} = (M_t - Y_{t-1}) \cdot P_{it} = (M_t - Y_{t-1}) \cdot \frac{\exp(V_{it})}{\exp(c) + \sum_j \exp\big(V_{jt}\big)}, \tag{4.4}$$

where *c* is a constant for the no-choice alternative and $M_t - Y_{t-1}$ is the total number of potential purchasers at time *t*. This number both includes first time purchasers and potential upgraders, and as shown in Jun and Park (1999), the method is easily extended to treat these segments separately.

Other studies combine the Bass diffusion model (as in 4.2) with a MNL model to simultaneously capture the diffusion and substitution processes in a multi-product framework. However, most of the studies we are aware of use aggregate demand models estimated on time series data on the market share. Weerahandi and Dalal (1992) use a disaggregate demand model, but with only two disaggregate variables.

Jun and Kim (2011) suggest a procedure, where purchase occasions for first time purchases are modelled with a Bass model and purchase occasions for replacement purchases are modelled with a replacement model. At each purchase occasion, the decision to purchase and the conditional decision about which product to purchase are modelled with a choice model. Consider one product with several product categories. The number of first time purchases is then:

$$F_{jt} = (M_t - Y_{t-1})\left(p + q\frac{Y_{t-1}}{M_t}\right) \cdot \Pr(B_t) \cdot \Pr(j_t|B_t), \tag{4.5}$$

where the parameters and variables in the Bass model are as before, $\Pr(B_t)$ is the probability of an actual purchase B taking place at time t and $\Pr(j_t|B_t)$ is the probability that the j'th category is chosen given the fact that the purchase takes place. The systematic components of purchase utility and alternative choice utility, respectively, are specified as $V(B_t) = \gamma + \alpha \cdot W_t$ and $V(j_t) = \beta' \cdot x_{jt}$, where the parameter γ is a constant, W_t is a vector of explanatory variables that explains the choice to buy the product and α is a vector of coefficients. The parameters in the vector β are preferences for the characteristics (x_{jt}) of the alternatives. With this they show that the number of first time purchases can be calculated as:

$$F_{it} = (M_t - Y_{t-1})\left(p + q\frac{Y_{t-1}}{M_t}\right) \cdot \frac{\exp(\alpha' \cdot W_t) \cdot \exp(\beta' \cdot x_{it})}{\exp(\gamma) + \exp(\alpha' \cdot W_t) \cdot \sum_{\mathrm{j}} \exp(\beta' \cdot x_{jt})} \tag{4.6}$$

The idea presented and applied in Paper 3, consists of using both market data and hypothetical SP data in a combined diffusion/substitution framework like those presented above. We envisage that the diffusion effect can be one of the reasons behind the delay of EV market penetration. At the same time, the characteristics of EVs and the recharging options play a crucial role in explaining individual choices to purchase an EV, but current diffusion models poorly represent the substitution effect among car types.

5 SUMMARY OF THE PAPERS

5.1 PAPER 1: A LONG PANEL SURVEY TO ELICIT VARIATION IN PREFERENCES AND ATTITUDES IN THE CHOICE OF ELECTRIC VEHICLES

Authors: Anders Fjendbo Jensen, Elisabetta Cherchi and Juan de Dios Ortúzar.

Presented at the XVII Congreso Panamericano de Ingeniería de Tránsito, Transporte y Logística (PANAM), Santiago, Chile, September 24-27 2012.

Published in *Transportation* vol. 41, issue 5, pages 973-993, 2014, DOI: 10.1007/s11116-014-9517-6.

This paper describes the methodology we set up to gather appropriate data to study the impact on individual preferences and attitudes, when individuals obtain real-life experience with electric vehicles (EVs). We used stated choices (SC) to elicit individual preferences because EVs and their associated charging infrastructure are not yet fully integrated on the market. Beside the EV alternative, the choice experiment included a conventional internal combustion engine vehicle (ICV) and a no-choice alternative. We also measured attitudinal effects (AE) that might affect the choice of an EV by individuals. Furthermore, to measure the extent to which the experience of using an EV may affect individual preferences and attitudes and their effect on the choice, we set up a "long panel" survey, where data was gathered before and after individuals experienced an EV in real life during a period of three months. Although there are many papers about data collection to study individual preferences for EVs, to our knowledge this is the first time that long panel data is used to measure the evolution of preferences and attitudes for EVs as individuals obtain experience with the product. Furthermore, in contrast to most previous studies, the methodology elicits detailed information about preferences for several relevant charging options.

Our results show that preferences and attitudes are indeed affected by real-life experience. In the SC experiment, the respondents only chose an EV half as often after real-life experience compared to the situation before. Both without and with experience, respondents choose the EV alternative more often if they had indicated a smaller car class for their next car purchase. Furthermore, we measured a change in attitudes for statements regarding the use of EVs. On the whole, respondents developed a more positive view of the driving performance of EVs and this change is significantly larger for women than for men. However, respondents express greater concern about being able to maintain their current mobility with an EV.

We conclude by highlighting how the measured effects can be used for policy recommendations. First of all, our results suggest that EV forecasts cannot be based on individual preferences estimated from a sample without real-life experience. Furthermore, that EVs are fun to drive and easy to recharge, should be communicated to potential consumers (especially women), as we found that participants with more experience had a more positive view on these aspects. Finally, EVs should be targeted towards consumers of smaller cars at the stage of market introduction, as these potential consumers indicated a higher preference for the EV alternative in general.

5.2 Paper 2: On the stability of preferences and attitudes before and after experiencing an electric vehicle

Authors: Anders Fjendbo Jensen, Elisabetta Cherchi and Stefan Mabit.

Presented at the *XIII International Conference on Travel Behaviour Research* (IATBR) Toronto, Canada, July 15-20, 2012.

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DOI: http://dx.doi.org/10.1016/j.trd.2013.07.006

In this study, we investigate the extent to which individual preferences and attitudes change after respondents gain real-life experience with an EV in their daily life and how these changes affect their behaviour. In particular, the objective of the paper is to test if the real-life experience affects (1) individual preferences for specific characteristics of EVs; (2) the overall preference for EVs versus conventional cars; (3) the individual's attitude towards the environment and (4) its effect on the choice of EV. We use a two-wave stated choice experiment collected during the pilot phase, as described in Paper 1. The sample consists of 369 individuals in possession of a driver's license, living in households with cars, who applied voluntarily to participate in the experiment. We estimated a hybrid discrete choice model, which accounts for panel correlation across observations of the same individual, using jointly the data collected before and after the respondents experienced the EV. The joint estimation allows us to compare individual preferences and attitudes and their effect on the choice between the two waves directly, after controlling for scale differences between the two datasets.

The results show that individual preferences indeed do change significantly after real-life experience with an EV as part of daily life. In particular, there are major changes in the preferences for driving range, top speed, propulsion costs, battery life and charging in city centres and at train stations. In line with other studies, we find that environmental concern has a positive effect on the preference for EVs both before and after the test period, but the attitude itself and its effect on the choice of vehicle do not change.

Our results suggest that the possible concerns consumers may have related to EVs, especially with regard to the driving range, increase after real-life experience. This could be caused by a mismatch between the driving range individuals wish to have available in their everyday lives and what is provided by EVs. Moreover, we focused on locations of the recharging infrastructure. We found that the possibility to charge at work, the number of battery stations in the road network and general charging locations in the public space are important attributes when studying the demand for EVs. Charging infrastructure could be an important area to focus on, to make up for the lower driving range that EVs provide. Charging infrastructure options should therefore be described as detailed as possible when trying to elicit preferences for this alternative as done in this stated choice study.

5.3 PAPER 3: EXPLORING DIFFERENT SOURCES OF VARIATION IN INDIVIDUAL PREFERENCES FOR ELECTRIC VEHICLES

Authors: Anders Fjendbo Jensen and Elisabetta Cherchi.

Working paper, DTU Transport.

In this paper, following the work published in Paper 2, we study the effect of real-life experience on individual preferences and attitudes further by exploring different sources of variation in preferences for electric vehicles (EVs). In this paper we mainly use the data collected for the final survey, as it is similar to but richer than the data collected in the pilot. As mentioned in Paper 1, the choice experiment in the first application was built with an orthogonal design, whereas the choice experiment in the second application was built with efficient design. Otherwise the surveys were similar but there were a few changes in the attributes of the choice experiment, the background variables and the attitudinal statements, just as the second application had a no-choice alternative in the SC. Moreover, in the final survey, all individuals who applied to participate in the demonstration project were invited to answer wave 1 of the survey, but only those who were actually chosen to participate knew that they were going to receive an EV for three months. This allows us to extend the analysis in several directions. In particular the paper investigates (1) the effect of the scale coefficient parameterisation; (2) the effect of respondents' knowledge about being selected; (3) the effect of the latent variable, scepticism and (4) differences in the results obtained with orthogonal and efficient design. Furthermore, the similar configuration of the two surveys allows for a validation of the estimated results by comparing similar models estimated on the two data sets.

To the extent it is possible with the changes discussed above, we used the same model framework as defined in paper 2. We found that with more real-life experience, only preferences for the EV alternative change and in particular, the preference for driving range and conventional charging (as opposed to quick charging) in city centres increased significantly. When testing whether there is a difference between those who knew they were selected to participate in the EV demonstration project and those who did not, we found that those who knew indicated stronger preferences for propulsion cost, EV driving range and the number of battery stations. In general we did not find any scale differences between the before and after data, and we did not find a reason to parameterise the scale parameter. Finally, we found that individuals who are more sceptic (conservative) indicated lower preferences for EVs before the real-life experience, whereas this effect was not significant after the experience. Similar results were obtained for models estimated on orthogonal and efficient design.

5.4 PAPER 4: PREDICTING THE POTENTIAL MARKET FOR ELECTRIC VEHICLES

Authors: Anders Fjendbo Jensen, Elisabetta Cherchi, Stefan Mabit and Juan de Dios Ortúzar.

Presented at the 93rd Annual Meeting, Transportation Research Board (TRB), Washington, USA, January 12-16, 2014 (Conference Proceedings)

Working paper, DTU Transport.

A well-known problem related to the prediction of the potential market for EVs, is connected to the fact that most discrete choice models for new technologies rely on hypothetical stated preference (SP) data. If this data is collected from respondents without much experience with EVs, the elicited preferences might not represent the true preferences when the general public has obtained real-life experience with the product. Furthermore, for forecasting, information about revealed demand is crucial to reproduce the aggregate baselines (i.e. the value of the ASC in the current year) and to re-calibrate the model for the future years. Consequently, many studies on EVs using SP data only present model estimations and/or trade-offs between coefficients and do not provide forecasts. Furthermore, when predicting the market for new products it is furthermore often necessary to account for how the product penetrated the market over time through a diffusion process. Previously such diffusion models have been combined with choice models to account for both diffusion and interaction across products, but so far this method has not been applied to the EV market.

This paper discusses the problem of predicting market shares for new products and suggests a method that combines a choice model with a diffusion model to take into account that new products often need time to obtain a significant market share. We use choice models estimated using SP data to simulate the EV market share in Denmark in 2020. We use the same model structures discussed in papers 2 and 3, though we did not include the latent effects, as this opens a different kind of discussion with respect to prediction. We use a model estimated on data from inexperienced respondents and a model estimated on data from the same respondents when they had obtained three months of experience with EVs and compare the market shares predicted with these models for the same scenarios. In order to calibrate the forecasting model to the Danish car market, we use monthly Danish sales data from 2008 to 2013.

The results show that the model estimated on respondents with real-life experience produces what appear to be more realistic market shares when no calibration is done. However, if we simply calibrate the ASC based on aggregate real market data for the base year, both models are unresponsive to future changes in the attributes, due to the major adjustment of the constants. The combined diffusion/choice model overcomes this issue since accounting for the diffusion effect allows for a slow penetration during the initial years and a faster market share increase as the EV market becomes more mature.

6 CONCLUSION AND PERSPECTIVES

This study was conducted during a period which is extremely important and interesting with respect to EVs. In early 2011, when the thesis project was initiated, only a few EVs were available and most of them were very small, not highway-capable and the quality in general was far from that of conventional cars. Shortly thereafter, the same year, a few highway-capable EVs such as the Mitsubishi ImiEV and the Nissan Leaf were introduced, and today, in 2014, several of the major car manufacturers such as Volkswagen, BMW, Audi, Mercedes, Chevrolet and Kia are introducing EVs. For many years EV market penetration has been believed to be just around the corner, but now it actually seems to be happening, at least on the supply side. On the demand side, however, the EV still has a marginal market share in most countries, with a few exceptions like in Norway, where EVs made up more than 10% of new car sales in the last two months of 2013. The need to study what drives the demand for EVs is greater than ever and the topic is being investigated widely across the world. A common way to elicit individual preferences and attitudes for EVs is to collect stated preference data as there are still too few EVs to observe revealed behaviour. However, in such hypothetical settings, respondents are presented with an alternative they do not have experience with and this far, there is no established way of using SP data for forecasting. This thesis contributes to the research in the following ways:

Firstly, it provides a detailed and robust survey methodology which can be used to elicit consumer's preferences towards EVs and attitudes that are relevant in the context of EVs. The methodology not only deals with how the variation in EV characteristics as well as respondent characteristics and attitudes affect the behaviour, but also how the level of experience affects behaviour. This was only possible in connection with a large demonstration project, which is of course quite comprehensive and expensive to conduct. However, we show that experience is important in several ways and the behaviour towards EV purchase cannot be expected to be constant as the population obtains more knowledge about the product. In particular, individuals indicated more positive attitudes towards the driving performance of EVs as they gained real-life experience. However, they were also more concerned about whether they would be able to maintain their current mobility with an EV. The latter seems to be the most important issue, since, in the choice experiment the EV was chosen less often by the sample with real-life experience. As EVs and knowledge about EVs diffuse in the population, there will be simpler and cheaper methods to obtain preferences and attitudes from a population with experience. This might begin to be possible in Norway, but in several countries where the EV market share is still marginal, demonstration projects or other ways to give users real-life experience are necessary.

Secondly, the thesis explores several different sources of variation in individual preferences for EVs. In particular, the thesis investigates differences in preferences and attitudes before and after EV experience. The choice between an EV, an ICV and a no-choice alternative is modelled jointly on before and after data with hybrid choice models, taking into account scale differences between the data sets. Results show that preferences for several attributes change significantly as the respondents obtain more experience with EVs. Furthermore, it shows that the attitudes of environmental concern and scepticism both have an effect on the choice between EVs and ICVs and that only the effect of scepticism changes with real-life experience. Finally, results show that the survey situation was important for the preferences, as we found differences in preference between those who already knew they were accepted for participation in the demonstration project and those who did not. We did not find any scale differences between the data collected before and after real-life experience with EVs.

Thirdly, the thesis discusses how the collected data can be used in forecasting. We present and apply an integrated choice model and diffusion model framework to forecast future scenarios for the market of EVs that properly accounts for the fact that new products usually need time to obtain a significant market share.

The assumption is that individual preferences are better measured using data from choice experiments. Therefore the model utilises the parameters obtained from the discrete choice model estimated in this thesis. However, the scale, the alternative specific constants and the diffusion effects are estimated in the joint discrete choice/diffusion model using monthly EV sales data in Denmark from January 2008 to January 2014. We present and compare the forecasting results of the method with an uncalibrated model and also compare the results of using the parameters estimated for wave 1 and wave 2. Even though the data did not allow us to estimate a precise effect of the diffusion, we show that the model allows us to include this effect in the model in order to obtain a better prediction.

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THE ARTICLES

A LONG PANEL SURVEY TO ELICIT VARIATION IN PREFERENCES AND ATTITUDES IN THE CHOICE OF ELECTRIC VEHICLES

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ABSTRACT

This paper describes the methodology we set up to gather appropriate data to study the impact of real life experience with electric vehicles (EVs) over a relatively long period of time on individual preferences and attitudes. We used stated choices (SC) to elicit individual preferences because EVs and their associated charging infrastructure are not yet fully integrated onto the market. Furthermore, to measure the extent to which the experience of using an EV may affect individual preferences and attitudes, we set up a "long panel" survey, where data was gathered before and after individuals experienced an EV in real life during a three-month period. We also measured attitudinal effects (AE) that might affect the choice of an EV by individuals. To our knowledge, this represents the first example of a "long panel" SC/AE and the first attempt to measure the formation of preferences and attitudes for this emerging product. Our results show that preferences and attitudes are indeed affected by real life experience. In the SC experiment, the respondents only chose the EV half as often as compared to the situation where they had not yet tried it. Furthermore, we measured a change in attitude for statements regarding the use of EVs. On the whole, respondents got a more positive view of the EV driving performance and this change is significantly greater for women than for men. However, respondents expressed more concern about being able to maintain current mobility with an EV.

The data gathered in this survey should also serve to analyse the changes generated by direct experience with EVs, and eventually to formulate and estimate advanced discrete choice models that allow insights into factors relevant for improved understanding of market behaviour.

1 INTRODUCTION

The transport sector is responsible for an increasing share of carbon dioxide emissions worldwide. This has boosted the focus on more environmentally friendly vehicles such as the electric vehicle[1] (EV). As EVs currently arriving on the market have much better driving performance than those of the early 1990's, their potential market penetration is higher than before. However, most people still do not consider them as a real alternative to the traditional gasoline car so it is important to understand in more depth, the reasons for this problem.

Several papers have studied the characteristics of green vehicles (see for example, Batley et. al., 2004; Bunch at al., 1993; Potoglou and Kanaroglou, 2007; Mabit and Fosgerau, 2011). In all these studies, typical stated preference (SP) experiments were presented to respondents who had no experience with the new alternatives investigated. Kurani et al. (1996) expressed scepticism on SP methods used for EV analyses. They suggested that it is not possible for consumers to have preferences for attributes such as limited driving range, home charging, zero tail pipe emissions and other unique attributes of EVs, because they have not experienced them first hand, and therefore have not been able to construct adequate preferences. With new technologies there might be a misconception about the impact that certain characteristics of a new product can have on the individual's daily life. However, people revisit and alter their preferences when actually encountering a new domain (such as when new alternatives enter the market or existing alternatives are completely overhauled): they are forced to rethink their choices. Hence SP methods are suitable to measure preference formation (see the many studies on inertia effects, i.e., Morikawa 1994; Bradley and Daly 1997; Cantillo et al., 2007; Cherchi and Manca, 2011).

Recent studies have also shown that besides objective characteristics, variables such as attitudes and perceptions that are not directly observable, can affect individual behaviour. A few papers (Bolduc et al., 2008; Daziano and Chiew, 2012; Daziano and Bolduc, 2013; Glerum et al. 2014) have studied attitudes specifically regarding the choice of new car technologies, but there is no evidence of how direct experience with an EV affects individual preferences and attitudes. Research in psychology and behavioural economics suggests that preferences are formed by experience and, as such, they can also change after individuals have, for example, tried an EV. It is therefore important to study if and how preferences and attitudes are affected when individuals directly experience an EV, as this will have an impact on the potential market penetration of EVs. However, the data typically used in demand modelling is not suitable for this purpose, since real panel data is not available. This is due to the current small EV market. SP data, as used in the literature so far, does not allow measuring the effects of real experience. Work from field experiments (Bamberg, et al., 2003; Fujii and Kitamura, 2003; Thøgersen and Møller, 2008; Meloni, et al., 2009), allows measuring specific factors but does not allow quantitative estimation of individual preferences .

This paper describes the methodology we set up to measure the extent to which real experience with an EV affects individual behaviour. The methodology consists of a "long panel" survey where data on both stated choices (SC) and attitudinal effects (AE) were gathered, both before and after individuals had experienced an EV in real life for a three-month period. To our knowledge, our work represents the first example of a "long panel" SC/AE survey and one of the first attempts to measure the formation of preferences for this product. Previous studies in Sweden (Gärling and Johansson, 2000) and in Berlin (Cocron et al., 2011, Franke et al., 2012, Franke and Krems, 2013) carried out interviews before and after the respondents obtained real experience with EVs. However, these papers only measure individual's attitudes and intentions and do not specifically focus on the survey methodology.

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[1] Many new vehicle technologies use electric motors together with different types of propulsion (i.e. hydrogen, gasoline/battery hybrid). In this study we focus on pure battery electrically-propelled vehicles.

As in previous studies on emerging vehicle technologies, we collected SC data because the EV alternative and the charging infrastructure are not yet fully developed on the market. The majority of previous studies on this subject have focused on the objective characteristics of vehicles (i.e. performance, purchasing and operating costs and driving range). A few studies have analysed the effect of charging speed (Ewing and Sarigöllü, 1998; Brownstone et al., 2000; Hidrue et al., 2011) while several studies (Bunch et al., 1993; Batley et al., 2004; Horne et al., 2005; Potoglou and Kanaroglou, 2007; Bolduc et al., 2008; Achtnicht, 2012; Hackbarth and Madlener 2013) have included fuel availability, mostly as a percentage of conventional fuel stations where it is possible to charge the batteries, but to our knowledge no paper has studied in depth the effect of different charging options for EVs on their potential market. Considering the relatively short EV driving distance, the available charging locations and charging types (charging speeds depend on type of charging) may have a major impact on the mobility of households. Charging the batteries of an EV is time-consuming, but it can take place at many different locations if the relevant infrastructure is available. It is then crucial to get more knowledge about individuals' preferences on charging speeds and charging locations in order to study to which extent they may affect market share. For this reason, in our SC experiment we accounted for charging locations and charging types in particular.

The rest of the paper is organized as follows. Section 2 describes the methodology followed to set up the "long panel" SC/AE survey. Section 3 reports the description of the SC experiment, with particular emphasis on the work done to define charging characteristics. Section 4 reports the description of the attitudinal survey and Section 5 describes how it was implemented and discusses the first results obtained. Finally, Section 6 summarizes our main conclusions.

2 METHODOLOGY

Long panels are typically gathered using revealed preference (RP) data. They consist of repeating the same survey (i.e. with the same methodology and design) at different times, for example once or twice a year for a certain number of years, or before and after an important event[2]. Our methodology consists of a long panel survey where individuals were interviewed before and after they had experienced an EV in real life for three months. As opposed to typical long panel data, we used a stated choice (SC) survey instead of the typical RP survey, because there is no real EV market yet. Although the methodology designed to gather the SC panel dataset is not different from that used in the case of RP data (Yáñez et al., 2009), the specific objectives of our panel, to test the effects of the three-month experience with an EV, raised some new interesting issues.

The first issue refers to sample selection. Our research was part of a larger project[3] that had several objectives other than estimating individual preferences. Balancing the different objectives, it was decided to select the sample based on voluntary participation. A large campaign was launched and advertisements sent out in the local press of 27 Danish municipalities. The advertisements included a brief presentation of the project and invited people to apply online for an experiment where they would receive an EV to use free of charge for a period of three months. Households would have the EV for three months and then the vehicle would be moved to another household. Most EVs used were the so called "triplets", i.e. the Mitsubishi ImiEV, the Citroën C-Zero and the Peugeot I-on, which are basically the same car.

It is important to mention that the reference population for our sample was formed by respondents older than 18 years, belonging to families owning at least one car and living in households with a dedicated parking

[2] Panels can be classified into two categories: "long survey panels" and "short survey panels". The latter consider multi-day data where repeated measurements on the same sample of units are gathered over a "continuous" period of time (e.g. seven or more successive days), but the survey is not repeated in subsequent years as in the former case.
[3] We refer to the project called "Test-en-elbil" run by the Danish EV provider Clever, which was financed by several partners including municipalities, governmental authorities and energy providers.

space. The sample of individuals was randomly selected from those who fulfilled the requirements among the individuals (more than 25,000) who had registered. Another issue peculiar to our panel concerns the time frame specified to complete the survey. The deadline was set shortly after the trial period (i.e. a maximum of 15 days), as we wanted individuals to have collected enough experience (almost the full three months) and record it while it was fresh in their memory. At pre-testing we experienced that too short a time frame to answer the second wave of questions caused drop outs (attrition bias)[4].

- The long panel survey was structured in two waves, collected over a three-month period:
- In the first wave, participants were asked to complete an internet survey, consisting of background information, a customised SC experiment and a set of attitudinal questions.
- After the survey was completed, the respondents received an EV, which they were able to use for three months as if it was their own.
- During the last 15 days of the three-month period, respondents were asked to complete the SC scenarios and attitudinal questions again. This was exactly the same survey that had been completed in the first wave, except for the background data which was not included a second time.

The internet survey consisted of four sections:

- A questionnaire on household vehicle ownership and use, definitions on the most likely future vehicle purchase and information on whether this new car would replace an existing one or if it would be an additional one for the household. Previous studies have shown that households with several cars are more likely to purchase an EV (Hensher, 1982; Kurani et al., 1996; Ramjerdi and Rand, 1999), because the household will be able to use another car for longer trips.
- A customised SC experiment based on the information collected in section 1. We chose to include the SC experiment as early as possible. The SC is the most important task of the survey and we wanted to prevent respondents getting exasperated due to the previous tasks.
- The third section, which was only included in the first wave, was dedicated to gathering standard socioeconomic information such as age, gender and level of education. This data enabled us to identify the population segments expressing different preferences when it was integrated in the discrete choice models. It was included between the SC experiment and the attitudinal statements, to avoid correlation between the car choices and the response to these statements.
- Finally, respondents were asked to indicate their level of agreement with a number of statements regarding new technologies, the environment, car interest and EVs in general.

A stand-alone web-survey application was developed specifically to collect the data. Internet surveys offer great flexibility in the use of interactive functions, which can help to communicate the necessary information to respondents and frame the questions on the basis of the previous answers (Iragüen and Ortúzar, 2004). This is especially useful in our long panel survey where (i) each wave had to be completed within a specific time, before and after the EV trial period, (ii) reminders needed to be sent out if a complete answer had not been registered within the defined time frame and (iii) information in the second wave needed to be linked to the answers provided in the first wave. Internet surveys have some drawbacks, as the lack of personal contact with respondents during the interview can generate misunderstandings and misuse. To avoid misunderstandings we included several explanations and graphics and we tested the survey in several pilot tests to make sure that respondents understood the tasks. For the background data, we included a number of

[4] We tested different time frames finding that if people were given too short a time to answer the survey a lower response rate was obtained. We believe this problem might have occurred in the first wave (although we did not test it); in subsequent waves of panels motivation usually decreases and this could have been especially the case here because individuals had already received the EV. Finally, another reason for attrition in our case could be a failure in sending reminders for the second wave.

controls to avoid meaningless answers. Furthermore, we included controls to make sure that exactly the same individual answered the survey before and after the testing period. To avoid misuse, each individual was provided with his/her own personal reference number, which could only be used once, and only within the assigned time frames.

The data collection process was divided into two phases. First, an experiment based on an orthogonal design allowed us to gather a large sample used to carefully test the attributes, the methodology and, more importantly, providing us with robust priors to build the efficient design (results can be found in Jensen et al., 2013). Based on the results of this first phase, a couple of changes on the type of attributes and on the attribute levels were defined before building the efficient design. Priors for the new attributes were obtained from a small pilot study using an efficient design. Since the scale might be different between the two models, we adjusted the parameters based on the purchase cost estimates. Two further pilot tests were then carried out specifically to test the efficient design.

3 STATED CHOICE EXPERIMENT

The SC experiment consisted of binary choices between a conventional car (gasoline or diesel) and an EV. Before the SC tasks, respondents were asked to state some details about their most likely next car purchase. More specifically, they could choose between seven car classes (Mini, Small, Intermediate, Standard, Multi Purpose Vehicle (MPV), Large and a final class called "other", if none of the previous six car classes fully described the household's desired car class) and two propulsion types (gasoline or diesel). This generated 14 possible segments. The attribute values shown to respondents were customised according to the likely car class and propulsion type. If some car classes shared several characteristics we used the same design for them (however, it was still important to distinguish the car classes when presenting them to the respondents). Therefore, an efficient design was optimised based on the defined attributes and levels for only 10 segments.

Respondents were also asked to assume that they were in a purchase situation and that only the conventional vehicle and a comparable EV with the characteristics shown in the survey would be available at the car dealer. Other than that, respondents were asked to assume that the two cars were identical (note that the car class did not vary between scenarios[5]). Respondents were asked to select the alternative that would best fulfil their needs in the purchase situation defined earlier.

Before the SC survey, respondents were asked to read three pages explaining what an EV is, the charging options (see Figure 1) and their environmental effects. As discussed in the introduction, one of the major concerns when using SC experiments to study new options is that people might misjudge them due to lack of knowledge. For this reason, we felt that it was important to give a clear and impartial description of EVs before starting the survey.

An example of choice situation for a standard class gasoline car is shown in Figure 2. To avoid bias due to the placement (right or left) of each alternative, the positions were randomly shifted across individuals but not across each scenario (the latter was tested in a previous experiment but many respondents found it distracting).

[5] In other choice experiments car classes have been varied across choice tasks (i.e. Brownstone et al., 2000; Potoglou & Kanaroglou, 2007). In our survey we chose to elicit the purchase needs (and hence the car class) beforehand. We framed the experiment around the most probable future car purchase in the household, so respondents were not asked to consider a random car purchase.

3.1 Definition of vehicle attributes

After an extensive literature review and several pilot surveys, we decided to describe each alternative by its purchase and driving costs, driving range, environmental effects and, in the case of EVs, availability of different types of charging infrastructure.

The *purchase price* was defined as the full price paid for the car considering all taxes, duties and/or incentives from the government. The price levels chosen were based on the current prices of the vehicles' standard version in each car class. To keep the scenario realistic, the EV purchase prices reflected the higher values found in the market. However, we chose the attribute levels so that in some situations the EV would be cheaper than the conventional car. This approach seemed reasonable because the price of batteries is falling (U.S. Energy Information Administration, EIA[6]) and because, specifically in Denmark, the purchase price is reduced by government incentives (EVs are exempted from registration taxes, which are between 105 and 180%[7]).

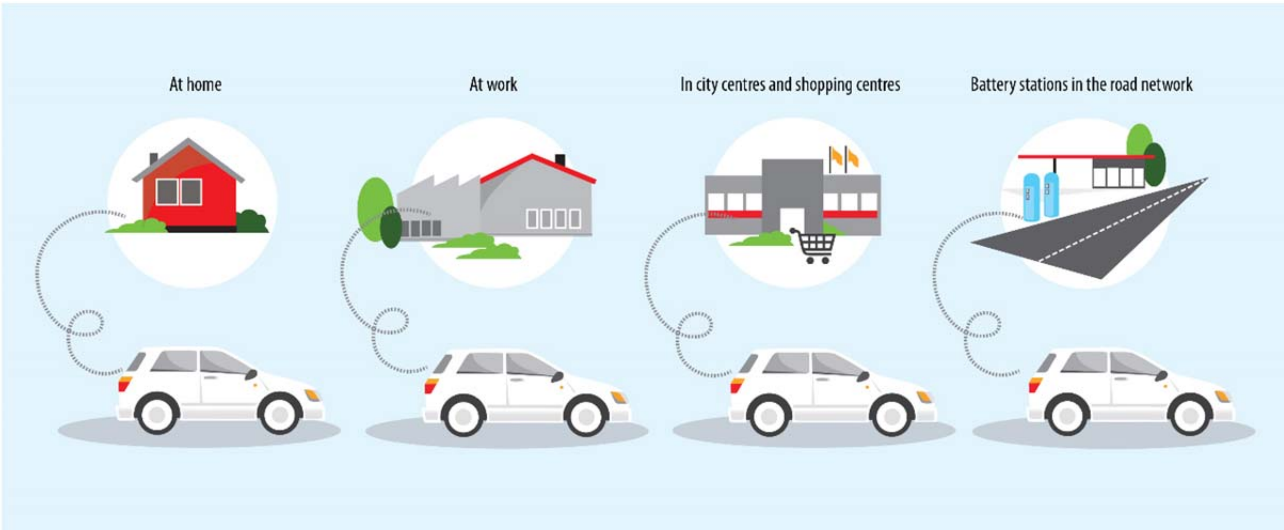

Figure 1: Illustration used in the survey to describe the different charging options for an EV

Driving costs were defined as the costs spent on fuel or electricity per km driven. To make the scenario more realistic, we also presented individuals with the effective driving cost, i.e. the cost calculated for the daily transport needs provided by the respondent earlier in the survey. Other marginal costs such as maintenance and vehicle depreciation can represent an important proportion of the average operational cost, but they are difficult to quantify and there is currently little knowledge about them for EVs. We therefore assumed these costs to be equal between the two alternatives and did not include them in the experiment.

The *driving range* was defined as the maximum distance that could be covered with a full tank or a fully charged battery. As discussed in the introduction, this characteristic represents one of the main limitations of EVs so we carefully discussed the levels shown to respondents. A high driving range could be considered

[6] http://www.eia.gov/todayinenergy/detail.cfm?id=6930
[7] However, EVs are not exempt from the 25% VAT.

unrealistic (as current EVs provide driving ranges from only 120 to 170 km in optimal conditions), so we set the maximum range to 200 km.

We described *environmental performance* as the amount of carbon dioxide emitted from the car per km driven[8]. The levels shown for the EVs reflected three scenarios: the current one[9] (as of 2011), one where EV emissions are half of the actual emissions, and one where there are no emissions. According to *energinet.dk,* in 2011 33% of the Danish electricity production was based on renewable energy, increasing to 41% in 2012. The Danish government has set the goal that all electricity production will come from renewable energy sources in 2050 (Danish Ministry of Climate Energy and Building), meaning that there should be no carbon dioxide emissions from driving an EV.

Scenario 1 of 6

Suppose that the car dealer has a gasoline version and a similar electric vehicle available with the features shown below.

Assume that the two vehicles are otherwise identical in terms of size, interior space and equipment

	Gasoline car	Electric car
New car, Small		
Purchase price *Price for a standard version without special equipment*	165.000 kr	264.000 kr
Driving costs *Expenses for fuel or electricity*	0,66 kr / km *Corresponding to 33 kr for your daily transport needs*	0,29 kr / km *Corresponding to 15 kr for your daily transport needs*
Operation range *The distance it is possible to drive on a full tank or fully charged battery in optimal conditions*	812 km	200 km
Carbon emissions *The total emissions per km of driving*	84 g/km	60 g/km *The amount of electricity from renewable energy sources is like today*
Infrastructure		
At home *We assume that a private charging facility is installed at home*	Not available	Full capacity obtained in 7 hours
In public spaces *General access to propellant in public spaces*	Not available	In 20 minutes, 110km driving is obtained Available in CITY CENTRES
Stations at the road network *Access to propellant at the road network*	Full capacity reached in 5 minutes Available at ALL gas stations	Full capacity reached in 5 minutes Available at 100 Battery stations  (Click to see locations on a map)
What car would you choose in this situation?	○	○
or		
If these alternatives are the only options available, I would not choose any of them	○	

Figure 2: Example of a choice situation

Other vehicle attributes were considered and discussed but not included in the choice experiment. Battery life was tested in some of our pilot surveys and found to be significant. However, with improved battery

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[8] For fossil fuels there is a direct connection between carbon dioxide emissions and fuel consumption and, thus, driving costs. We considered fuel costs and carbon dioxide emissions as independent attributes to identify the pure effect of each of them.

[9] The carbon dioxide emissions for the current scenario ranged from 50g/km for the smallest car class to 70g/km for the largest car class.

technology this is not as large an issue as with earlier battery technologies[10]. We decided, therefore, to leave it out and asked respondents to assume that maintenance costs were the same between alternatives. Similar studies have also presented some kind of performance attribute, such as acceleration (Potoglou & Kanaroglou, 2007; Mabit and Fosgerau, 2011) or top speed (i.e. Dagsvik et al., 2002; Batley et al., 2004). However, due to the improved battery technology, modern EVs provide better driving performance, so we assumed that there was no difference between EVs and ICVs in this respect. Free parking is a political incentive that turned out to be significant in Adler et al. (2003) and Potoglou and Kanaroglou (2007). We decided, however, to omit it since it is mainly an issue for drivers in city centres, who represent only a small part of our sample.

3.2 DEFINITION OF CHARGING ATTRIBUTES

Much effort was put into defining relevant charging opportunities. Based on current developments in charging infrastructure for EVs, the focus for available charging infrastructure was put on two charging options: *Battery stations* and *Charging in public areas*. Since all respondents in our sample had the possibility to install a charging device on a private location, for all choice situations, we assumed that it was possible to charge an empty battery to full capacity in seven hours at home.

Battery stations were defined as the number of locations where you would find a service for EV, comparable to the service currently found for conventional cars at fuel stations situated on the road network. The levels were defined as 0, 10 and 100 stations nationwide and the charging time was fixed to 5 min. This type of infrastructure renders longer trips possible without longer breaks and battery stations will usually be located on motorways or larger main roads. To make it easier for the respondent to evaluate the importance of this attribute and to ensure that the attribute was perceived as realistic, a map with the exact locations of the battery stations was shown for each choice scenario. The data was available from a parallel project regarding optimisation of the battery stations location (Nørrelund and Olsen, 2010).

Charging in public areas was defined as: 'the possibility of charging when the EV was parked in public parking places'. This charging option was presented as the combination of two different locations and two different charging speeds. The two general locations were city centres and shopping centres. By city centres we mean the historical city centre found in most Danish cities. By shopping centres we mean larger shopping areas (malls, do-it-yourself stores, and large warehouses) usually located outside cities and well known to all Danish residents. The two charging speeds were charging at a conventional charging pole/stand, where full capacity is obtained in about 2-3 hours[11] or charging at a much faster *quick charge* facility, where 80% capacity is obtained in about 20 min. Based on experience from the pilot studies we decided to present the attribute as: 'how far it is possible to drive after 20 min of charging' instead of explaining the different charging types in detail. If we had not done this respondents could wrongly assume that it was necessary to stay for the entire charging period, which is not useful for a person who would usually stay at such locations for shorter periods. By including the base option, "not available", the public charging attribute had five levels.

Charging at work was another attribute found to be significant in some of our pilot studies but omitted from the final survey because not all respondents travelled to work and further customization would have been necessary.

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[10]EV models introduced in the late 1980's used Lead-Acid technology which could often only be used for 300 cycles/15,000km. Modern Li-Ion batteries can be used for about 3000 cycles/1,000,000km (www.delk.dk).

[11]We assumed charging poles with 3 phase 16 amp.

3.3 EFFICIENT DESIGN

The efficient design was based on five attributes with three levels, and one attribute with five levels and 10 segments. A non-linear in the purchase price utility function was specified to account for possible income effect in the purchase (Jara-Diaz and Videla, 1987). Based on the priors from phase 1, it was possible to develop a reasonably efficient design. To take uncertainty into account, Bayesian priors were used, which means that the priors were considered (and modelled) as random rather than fixed parameters. We assumed that all priors had equal probability of being within two standard errors of the estimated parameter, except for the two cost coefficients the intervals of which were tightened to guarantee that microeconomic conditions were fulfilled. The uniform distribution was used to avoid long tails as these could imply that some draws gave rise to extreme parameter values[12].

The efficient design was generated with Ngene (ChoiceMetrics, 2011), using the RSC (Relabeling, Swapping and Cycling) algorithm. Thirty choice scenarios, which allow a level balanced design, were generated and divided into five "blocks", so that each individual had to answer only six of these. Different designs were built for each car class, using the heterogeneous design feature[13] of Ngene. A single combined asymptotic covariance (AVC) matrix was computed weighting each segment based on the most likely car class indicated in the earlier study with 713 respondents.

The designs were tested with simulated data. We assumed that the simulated individuals had the same utility function we had used to create the SC design, and added an extreme value type 1 (EV1) error term. Using a t-test against the true parameters (i.e. the parameters used to simulate the data), we found that all parameters were recovered at the 95% confidence level.

4 ATTITUDES AND PERCEPTIONS

To measure attitudes and perceptions potentially affecting individual preferences for EVs, our questionnaire included several statements to which respondents were asked to indicate their level of agreement using a five-point Likert scale (as most previous studies, except for Bolduc et al. (2008) who used a seven-point scale). Based on the responses obtained, a factor analysis was then used to cluster the indicator statements into relevant groups of attitudes or perceptions. Statements were defined based on previous literature (Mokhtarian et al., 2001; Vredin Johansson et al., 2006; Bolduc et al., 2008; Atasoy et. al., 2010) and on the type of latent effect we wished to measure with the discrete choice model. With the statements included, we are able to measure the effect of: *Environmental Concern* (EC), *Appreciation of Car Features* (ACF), *Technology Interest* (TI), *Pro EV attitude* (Pro EV) and *Scepticism* (Scep).

Environmental Concern is the attitude most typically measured in studies concerning EVs. Several studies have found that people who care more about the environment have a significantly higher preference for car alternatives with better environmental performance (see for example Vredin Johansson et al., 2006; Daziano and Bolduc, 2013). Early estimations from the pilot survey showed similar results for the choice between an EV and a conventional vehicle. The factor analysis conducted in the pilot already indicated a connection between environmental concern and preference for EVs, as several statements obtained high factor scores in both groups and with the same sign.

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[12] This could lead to an incorrect sign for the marginal utility. A test showed that there was little difference in efficiency for a specific design when evaluated with normally or uniformly distributed Bayesian parameters.

[13] Actually, this is called heterogeneous pivot design (ChoiceMetrics, 2011). The pivoting feature can be used to calculate the values pivoted around the reference values for each attribute automatically. However, it is necessary to include the reference alternative in the scenarios, which was not desired in this study.

We believe that a higher *Appreciation for Car Features* should reduce the preference for new car alternatives and therefore also for EVs. The factor analysis performed with the pilot survey already indicated this result, as two of the statements obtained high factor scores for both ACF and Pro EV, but with opposite signs.

Modern EVs come with some innovative technological solutions, such as regenerative braking, smart phone applications to follow the charging process or to find the nearest charging option. Therefore, it could be that people with a greater *Technology Interest* would also find EVs more appealing.

The *Pro EV* group included a number of statements specifically regarding the performance and use of EVs. A much improved battery technology means that EVs currently arriving on the market should not be affected by the problems of previous models introduced in the 80's and 90's. However, a negative perception of the technology caused by this reputation might result in individuals showing a lower preference for EVs. Later, we will see that respondents showed a more positive attitude towards EV performance as their experience with the vehicles increased.

The *Scepticism* group shows conservative behaviour with respect to new technologies, the environment and EVs. As they do not like change we would expect that people belonging to this group would show less interest in an EV.

5 RESULTS

The results presented here are based on 196 answers completed (i.e. people who answered the survey before and after they obtained real life experience with an EV). About 20 individuals refused to participate, after they were selected, due to changes in their status (divorce, disease in families, etc.) and problems with the EV used in the early stage of the project[14]. Interestingly, some of these dropped out of the project after they received the car because their driving needs changed dramatically and the EV could no longer meet their requirements. Among the comments reported during the pilot survey, it is interesting to note that some participants were surprised that their EV was not able to drive 150 km on a single charge (which is the stated driving range under optimal conditions[15]). A few also found that the lack of noise entailed an increased risk of accidents. Nevertheless there have been no accidents related to this problem in this particular project.

The 27 municipalities that participated in the project have 1.5 million inhabitants (in 917,000 families) aged 18 or over. With more than 25,000 applicants, this means that 1.7% of their population registered. We note that families with children are overrepresented in our sample, with a share of 77%, compared to 37% in the general population. As mentioned in Section 2, the reason for this is that families without a car are not represented in our sample and in Denmark 83% of families with children have a car, whereas only 52% of families without children have a car. Some descriptive statistics for this sample are shown in Table 1.

Given the voluntary application process there is a risk that the sample is biased towards people who are more interested in EVs, who have a higher concern for the environment and/or were just interested in having a free car. It is important, however, to recall first that only families that already owned a car were selected. Secondly, only 13% of the sample declared that they would like to buy a second car, while 75% declared that they would like to replace their current car. It is then reasonable to believe that they were truly interested in

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[14] At the beginning of the project, there were no "factory built" EVs available on the market. Hence, rebuilt Citroën C1 cars, where the combustion engine was replaced with an electric engine were used. Unfortunately these cars had many problems.

[15] There is a hefty debate about the driving range stated for EVs. The manufacturers use an EU standard calculation of the possible driving range, but often the actual driving distance is much lower due, for example, to driving at high speeds or in cold weather.

knowing how an EV performs to eventually consider it in their future purchase. Finally, households participating in the experiment were required to use the EV as the primary car during their participation. Unfortunately it was not possible to control if this condition was respected, but on average the EVs were used more than 50 days during the 3 months.

Table 1: Socioeconomic characteristics of the sample gathered in the first phase

Variable	Mean all DK pop. over 18 yrs	Mean 27 muni. pop. Over 18yrs	Mean sample	N sample	Std Dev sample	Min sample	Max sample
Age of respondent	48.7	48.6	46.41	196	9.37	19	73
Respondent is male	0.49	0.49	0.55	196	0.5	0	1
Number of family members	1.94	1.96	3.41	196	0.88	1	5
Share of families with children	0.37	0.37	0.77	196	0.42	0	1
Average number of children in families with children	1.78	1.79	1.74	151	0.52	1	3
Number of cars in car owning households	1.28	1.29	1.55	196	0.59	1	4
Annual km driven in household (all cars in the household)	-	-	32,490	196	16,299	8,000	92,000
Annual km driven in household (main car only)	-	-	25,347	196	10,774	8,000	70,000
Daily driving needs			49.9	195	42.7	0	200
Respondent's own income[16]	272	273	405	193	164	15	1,200
Number of times quick charge was used in the testing period			4.5	167	9.31	0	91
Number of days the EV was driven by the respondent in the testing period			51.77	185	27.6	0	125
Number of days the respondent was a passenger in the EV in the testing period			10.35	186	12.01	0	70
Purchase year for reference car (< 5 years ahead)	-	-	2013.7	161	1.18	2012	2016
Reference purchase five or more years ahead				13			
Reference purchase will replace current car				147			
Reference purchase is an extra car				27			
No future purchase, even in the longer term				22			

[16] In the survey we asked for the individual's gross income, while the average gross income for the Danish population is taken from the National Statistics where tax free services and share income are not accounted for.

5.1 ANALYSIS OF STATED CHOICES

With each person answering six choice scenarios in each wave, a sample of 2,352 SC observations was obtained. The choice shares presented in Table 2 indicate some of the variables that would be important to investigate at a choice modelling stage. At first sight, it would appear that individuals became more aware of some of the negative factors of EVs after having real life experience with them, since on average the EV was chosen in 31% of the scenarios in wave 1 and only in 17% of them in wave 2. The conventional car share increased from 46% to 58%, while the “none of these” option was selected in 25% of the scenarios in both waves.

Table 2: Shares of choices between the three options in the two waves

		Wave 1			Wave 2			Relative change		
	n	No Choice	EV	ICV	No Choice	EV	ICV	No Choice	EV	ICV
Men	648	22	32	47	25	17	58	0.14	-0.45	0.24
Women	528	25	30	45	26	16	58	0.05	-0.47	0.30
Single car family	432	26	23	50	28	12	60	0.07	-0.51	0.20
Multi car family	744	21	36	43	24	20	56	0.11	-0.44	0.31
EV driving range is 134 km	398/389	28	30	41	31	14	55	0.11	-0.53	0.31
EV driving range is 164 km	382/409	18	35	47	23	17	60	0.28	-0.52	0.28
EV driving range is 200 km	396/378	22	29	49	21	20	59	-0.06	-0.31	0.21
Purchase is Mini car class	210	3	53	44	19	25	57	5.49	-0.54	0.29
Purchase is Small car class	258	18	41	41	18	26	56	0.00	-0.37	0.37
Purchase is Intermediate car class	360	24	25	51	29	10	61	0.22	-0.60	0.20
Purchase is Standard car class	192	50	11	39	36	11	53	-0.27	0.00	0.35
Purchase is Large car class	42	19	12	69	14	7	79	-0.25	-0.40	0.14
Purchase is MPV car class	96	30	30	40	28	16	56	-0.07	-0.48	0.42
Purchase is other car class	18	0	17	83	22	22	56	-	0.33	-0.33
All	1,176	23	31	46	25	17	58	0.10	-0.46	0.27

Demonstration projects have previously been used to give consumers experience with EVs, and even though the methodologies used were different, results suggest a similar pattern. Based on direct questions about attitudes and willingness to purchase, for only eight families that participated in a demonstration project over three months, Gärling and Johansson (2000) measured a “somewhat” reduced willingness to purchase an EV as families obtained more experience with EVs. Similarly, in Franke et al. (2012), 64% of the sample indicated that they would intend to purchase an EV before they participated in the demonstration project, whereas this number was only 51% after three months’ experience with the EV. While there are no apparent differences between the choices of men and women, the purchase situation is definitely important for the choice. If the car purchase referred to the only car in the household, the EV was chosen in 23% of the scenarios in wave 1, but this increased to 36% if there were more cars in the household (that could be used for longer trips). For both groups the EV was chosen less in wave 2, but this decrease was slightly larger for single car families. The largest decrease in EV share between waves 1 and 2 occurred in the Mini car and Intermediate car classes.

5.2 ANALYSIS OF ATTITUDES AND PERCEPTIONS

Table 3 reports the results of the factor analysis performed on the final sample. Since respondents answered the attitudinal questions in both waves of the survey, we ran the same factor analysis on the data for each wave separately. We set the factor-loading threshold as 0.3. If an indicator belongs to a factor (i.e. if it obtained a factor loading above 0.3), then a + sign indicates a positive factor loading and a – sign indicates a negative factor loading. The columns B and A indicate if the result was obtained for the wave before (B) or after (A) the real life experience.

Table 3: Attitudinal statements and their factor group

		EC		TI		ACF		Pro EV		Scep	
		B	A	B	A	B	A	B	A	B	A
Employment is more important than the environment	q0	-	-								+
I do what I can to contribute to reduce global climate changes, even if it costs more and takes time	q1	+	+								
The authorities should introduce legislation that forces citizens and companies to protect the environment	q2	+	+						+		
Electric vehicles should play an important role in our mobility systems	q14	+							+		-
It is important for me to follow technological development	q5			+	+						
I often purchase new technology products, even though they are expensive	q6			+	+						
Citizens want to drive cars and we should expand the road network accordingly	q3		-			+					
I feel safer in a larger car	q7					+	+			+	+
I like the sound and power of a conventional car engine	q10					+	+				
I would pay more for a car with a nice design	q11					+	+				
The capacity of transporting people and luggage matters more in the choice of a car than its appearance	q12					-	-				
I would prefer a small car that takes less space	q13						-				
Electric vehicles are more reliable than conventional vehicles	q18							+	+		
It is more fun to drive an EV compared to a conventional car	q19	+						+	+		
EV accelerate faster than conventional vehicles	q20							+	+		
New technologies create more problems than they solve	q4				-					+	+
When using an EV, I think it would be inconvenient to have to remember to plug it in when the car is parked at home or at other locations	q15									+	+
I am concerned that EVs are not powerful enough to make a safe takeover	q16								-	+	+
If I use an electric vehicle instead of a conventional vehicle, I would have to cancel some activities	q17									+	+
The car's ability to accelerate influences my safety perception	q8										
I often forget to use the seatbelt when I drive a car	q9										

Obviously an indicator can belong to several factors. Interestingly, half of the statements in the *Pro EV* factor group are above the threshold in wave 2 only. An explanation could be that respondents in wave 1 had a neutral response to these statements since they did not have experienced an EV yet. This indicates that attitudes regarding EVs are not firmly grounded until after the test period. Two statements (q_8 and q_9 in Table 3) did not successfully group with other statements in this analysis. However, more observations might solve this issue.

To test if there are any significant differences in the responses to the attitude statements between waves 1 and 2, we set up a standard contingency table with the wave on one axis and the answer to the statement on the other. The difference in cell frequencies can then be tested with a χ^2 test to investigate any relation between these two categorical variables. Further, to gain an insight of the size and direction of a given change, we tested for difference in means between waves 1 and 2. The results are shown in Table 4.

Table 4: Difference in attitudinal response between waves
(1=highly agree, 5 disagree)

Group		Mean before	Mean after	Mean difference	Mean t-test	$\chi 2$ test
Environmental Concern	q_0	3.07	3.00	-0.07	-0.75	2.29
	q_1	2.58	2.66	0.08	0.94	2.67
	q_2	2.49	2.59	0.09	0.80	5.04
	q_{14}	1.85	1.94	0.09	0.97	1.72
Technology Interest	q_5	2.20	2.27	0.07	0.71	10.91*
	q_6	2.84	3.01	0.16	1.40	4.38
Appreciation of Car Features	q_3	2.53	2.57	0.04	0.43	1.54
	q_7	2.40	2.53	0.13	1.17	6.69
	q_{10}	3.14	3.40	0.26	2.17*	5.55
	q_{11}	2.92	2.98	0.06	0.52	2.07
	q_{12}	2.32	2.28	-0.04	-0.32	1.36
	q_{13}	2.97	2.92	-0.05	-0.47	1.06
Pro EV	q_{18}	2.95	3.04	0.09	1.17	19.70**
	q_{19}	2.78	2.39	-0.39	-4.18*	89.90**
	q_{20}	2.74	1.93	-0.81	-8.35*	96.93**
Scepticism	q_4	4.12	4.07	-0.05	-0.53	1.97
	q_{15}	3.45	3.78	0.33	2.68*	16.54**
	q_{16}	3.43	4.22	0.79	7.55*	104.67**
	q_{17}	2.93	2.02	-0.91	-7.28*	63.71**
	q_8	2.53	2.59	0.06	0.56	11.27*
	q_9	4.91	4.89	-0.02	-0.39	3.19

(*) P < 0.05, (**) P < 0.01.

For eight out of 21 statements, we found a significant difference in the cell frequencies between both waves, while the differences in mean were significant in six statements on a 5% threshold. However, we found significant differences in cell frequencies for only two statements (q_8 and q_5) that did not directly involve the performance or use of EVs. Statement q_8, *The car's ability to accelerate has an influence on my safety perception,* is about performance of cars in general. With a χ^2 statistic of 11.6 and four degrees of freedom, there is only a 2% probability that the deviation between the waves is due to chance only. The change in cell frequencies might be due to experience, as performance is highly reduced when the battery starts to run out of power. Such experience is rare with conventional cars and therefore the real life experience of using an EV might have changed this attitude (although no significant difference was found for the mean). Another statement where we found differences in cell frequencies is q_5, *It is important for me to follow technological developments*. Again, the cell frequencies were distributed differently, but no significant difference in the mean was found. For the statement q_{10}, *I like the sound and power of a conventional car engine*, we found no difference in cell frequencies, but on average, respondents agreed significantly less with this statement in wave 2. For the rest of the attitudes that did not directly involve the performance or use of EVs, we did not find any significant differences between the waves. Overall, EV experience does not affect *Appreciation of Car Features* (ACF) and *Environmental Concern* (EC) statements.

As expected, statements regarding the performance and use of EVs were particularly affected since many respondents in wave 1 had a neutral attitude towards them while in wave 2 they gained experience with them and formed their attitudes. Interestingly, respondents seem to have significantly more positive views about the driving performance of EVs in wave 2, which is shown by less concern about having enough power to make a safe takeover (q_{16}) and higher agreement to the statements *It is more fun to drive an EV compared to a conventional car* (q_{19}) and *EVs accelerate faster than conventional cars* (q_{20}). Regarding statements q_{15} and q_{17}, which focus on the everyday use of this alternative, respondents in wave 2 expressed significantly less scepticism about having to remember to charge the EV (q_{15}), but much more concern about being able to maintain their current mobility (q_{17}). The latter result is most probably due to the relatively short driving distance that current EVs provide compared to conventional cars. In fact, the highest absolute difference in average response between the waves was found for this attitude.

To go even further into this analysis, we investigated possible relations between population segments and changes in the level of agreement to each statement between waves 1 and 2. First, we tested, whether attitude changes differed by gender. For each statement, we calculated how many steps each respondent moved on the five-level Likert scale. A negative number means that the respondent agrees more with the statement in wave 2 than in wave 1 and vice versa. As before we then computed the mean of the difference between genders and performed a t-test. As the changes in level of agreement are categorical variables, we performed a χ^2 test to see if there was any difference in cell frequencies by gender. To avoid cells with a very low frequency, all steps higher than one were merged for each direction as seen in Table 5 with statement q_{16} as an example.

Table 5: Contingency table for changes in the level of agreement by gender to q_{16}
(- higher agreement, + lower agreement)

	-2 or more	**-1**	**0**	**+1**	**+2 or more**
Female	5 5.68%	8 9.09%	18 20.45%	27 30.68%	30 34.09%
Male	4 3.7%	3 2.78%	42 38.89%	30 27.78%	29 26.85%
Total	9 4.59%	11 5.61%	60 30.61%	57 29.08%	59 30.1%

Table 6: Average change in response between waves, classified by gender
(- higher agreement, + lower agreement)

Group		Mean female	Mean male	Mean difference	Mean t-test	$\chi 2$ test
Environmental Concern	q_0	-0.11	-0.04	0.08	0.53	3.54
	q_1	0.08	0.08	0.00	0.03	2.20
	q_2	0.17	0.03	-0.14	-0.86	3.01
	q_{14}	0.10	0.07	-0.03	-0.22	2.07
Technology Interest	q_5	0.07	0.06	0.00	-0.03	1.87
	q_6	0.09	0.22	0.13	0.79	4.81
Appreciation of Car Features	q_3	0.01	0.06	0.05	0.38	0.79
	q_7	0.38	-0.07	-0.45	-2.93*	9.04
	q_{10}	0.17	0.33	0.16	0.99	2.51
	q_{11}	0.18	-0.04	-0.22	-1.48	4.32
	q_{12}	-0.05	-0.03	0.02	0.11	4.77
	q_{13}	-0.16	0.04	0.20	1.21	7.38
Pro EV	q_{18}	0.07	0.10	0.03	0.27	4.92
	q_{19}	-0.58	-0.23	0.35	2.30*	11.33*
	q_{20}	-0.97	-0.68	0.29	1.59	7.76
Scepticism	q_4	-0.08	-0.02	0.06	0.43	4.59
	q_{15}	0.47	0.21	-0.25	-1.13	4.71
	q_{16}	0.83	0.75	-0.08	-0.41	10.22*
	q_{17}	-0.90	-0.93	-0.03	-0.13	0.48
	q_8	0.07	0.06	-0.01	-0.07	1.10
	q_9	0.10	-0.12	-0.22	-2.50	8.81

(*) $P < 0.05$, (**) $P < 0.01$

As seen in Table 6, we found that several attitudes changed differently with gender. In fact, for the statements *I feel safer in a large car* (q_7) and *I would like to pay more for a car with a nice design* (q_{11}), women agree less in wave 2 than in wave 1, whereas the response for men is stable. Moreover, for the statements *It is more fun to drive an EV compared to a conventional car* (q_{19}) and *EVs accelerate faster than conventional cars* (q_{20}), both segments agree more in wave 2 than in wave 1, but the difference between waves is significantly higher for women than for men. For q_{16}, *I do not think that EVs are powerful enough to make a safe takeover*, both segments agree less with this statement in wave 2 and there is no significant difference between them. However, the χ^2 test indicates a difference in cell frequencies, as men are more stable in their response than women. As shown in the contingency Table 5, almost 40% of men did not change their response to this statement, while only 20% of the women behaved in this way.

Even though an EV was available to each household during the testing period, there is a large difference between respondents in terms of how much experience was actually gained during the three months. Therefore, the actual level of experience with the EV might influence the change in response to some of the statements. As a measure of "level of actual experience", we used the data on how many days the EV was used during the testing period. As thresholds we set less than or equal to 60 days of use, as low level of experience, and more than 60 days of use as high level of experience. Although we found that both groups agreed significantly more with q_{20}, *EVs are more fun to drive than conventional cars*, in wave 2, based on the t-test the change is significantly larger for the more experienced group. For q_{17}, *If I use an EV instead of a conventional car, I would have to cancel some activities*, both groups also indicated a higher level of agreement in wave 2 but, again, if the respondent had more experience, the effect was significantly larger. Similarly, we tested if experience with the quick charging option had an effect on attitude changes. A total of 60 % of our sample indicated that they used the quick charging facilities at least once during the test period. In accordance with the previous result, this group agreed more with q_{20} (indicated by the t-test at the 90% level) and q_{17}. For this result also, a significant difference in cell frequencies was found for both statements.

6 CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper describes the methodology designed to gather appropriate data to study the potential market penetration of electric vehicles (EVs) in Denmark (accounting in particular for charging locations and charging types), and to test the impact of direct experience with such cars on individual attitudes and preferences. As in previous studies on emerging vehicle technologies, we collected stated choice data because the alternative and its accompanying infrastructure is not yet fully integrated onto the real market. We also collected data on individuals' attitudes to several issues that might affect the choice of an EV. The methodology consists of a "long panel" survey where data on both stated choices (SC) and attitudinal effects (AE) were gathered before and after individuals had experienced an EV in real life. Several pilot surveys provided valuable knowledge leading to several adjustments to attributes and survey functions in the final survey.

The data gathered serves to analyse the changes generated by direct experience with EVs and eventually to formulate and estimate advanced discrete choice models that should allow a more accurate assessment of their potential market penetration. In our experiment, the EV was chosen much less often after having experienced it, so it is important to investigate the reasons for this. Even without modelling results, this analysis allows us to highlight some interesting effects that can be used to inform policy recommendations:

- Policy forecasts cannot be based on individual preferences estimated from a sample without actual experience or without market references.
- Potential customers should be well informed about how EVs work. With more experience, respondents (especially women) tend to show a more positive attitude towards the driving performance of EVs and less concern about getting used to charging these cars. Hence, it is important to communicate such information (i.e. "EVs are fun to drive and easy to charge") to inexperienced users.
- On the other hand, our respondents expressed a greater concern about the ability to maintain their present mobility with an EV. Even though this clearly reflects the impact of some negative properties of these vehicles (i.e. too short a driving distance), these results should also be communicated to avoid negative publicity from owners who have had bad experiences. As the EV was chosen almost half as many times in wave 2 than in wave 1, this suggests that this factor is much more important than the improved perception of driving performance.
- The class of car that the customer wishes to purchase is important. In the SC experiment and in both waves, respondents looking for small cars chose EV more often than respondents looking for large cars. Therefore, for emerging EV providers it might be better to focus on smaller car classes initially. Analyses of the attitudinal statements indicate that experience with an EV does not change attitudes towards *Appreciation of Car Features* and *Environmental Concern*. However, model results showed that the latter plays a role in the preference for EVs (Jensen et al., 2013).

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ON THE STABILITY OF PREFERENCES AND ATTITUDES BEFORE AND AFTER EXPERIENCING AN ELECTRIC VEHICLE

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ABSTRACT

In this study, we investigate the extent to which experience affects individual preferences for specific electric vehicle characteristics, individual attitudes toward the environment, and the impact of the attitudes on the choice between an electric and a conventional vehicle. We use a two-wave stated preference experiment where data was collected before and after the respondents experienced an electric vehicle for three months. We estimate a hybrid choice model using jointly the stated choices before and after the test period. The results show that individual preferences indeed change significantly after a real experience with an electric vehicle in the household. In particular, there are major changes in the preference for driving range, top speed, fuel cost, battery life and charging in city centres and train stations. In line with other studies, we find that environmental concern has a positive effect on the preference for EVs both before and after the test period, but the attitude itself and its effect on the choice of vehicle does not change.

1 INTRODUCTION

The increasing focus on pollution produced by private vehicles has boosted the development of electric vehicles[1] (EVs) and interest in their potential market penetration. Most prior analysis has used stated preference data to elicit preferences towards EVs and their characteristics, with a few also accounting for latent attitudes that affect individual choices. Stated preference data are needed when a product is not fully available on the market, which is usually the case when studying new vehicle technologies. However, carefully customized, well designed and conducted, stated preference experiments on EVs are hypothetical settings where individuals express their preferences without having any true experience of the "product" they face raising scepticism over usefulness. In this paper, we investigate the extent to which individual preferences and attitudes change after individuals experience an EV in their daily life.

2 THE JOINT HYBRID CHOICE MODEL

A joint hybrid choice framework used is a latent variable model jointly estimated on a two-wave panel SC dataset. The model is a typical discrete choice model (Ortúzar and Willumsen, 2011) that incorporates latent variables to measure individual attitudes. The discrete choice model in our hybrid model is a mixed logit model that allows us to account for panel correlation among choices from the same individual in the SC dataset. Since we collected data in two waves, before and after individuals experienced an EV, the hybrid structures for each wave are jointly estimated to control for scale differences between the two datasets to compare individual preferences and attitudes between the two waves directly.

As in the typical discrete choice model, define U_{jnt}^{w} to be the utility that each individual *n* associates to alternative *j*, in choice task *t*, respectively before (*w=B*) and after (*w=A*) the experience with an *EV*. The joint model can be written as:

$$\begin{aligned} U_{jnt}^{B} &= ASC_{j}^{B} + \boldsymbol{\beta}_{jS}^{B}\mathbf{S}_{n} + \boldsymbol{\beta}_{jX}^{B}\mathbf{X}_{jnt} + \beta_{jAtt}^{B}Att_{n}^{B} + \mu_{jn}^{B} + \varepsilon_{jnt}^{B} \\ U_{jnt}^{A} &= \theta\left(ASC_{j}^{A} + \boldsymbol{\beta}_{jS}^{A}\mathbf{S}_{n} + \boldsymbol{\beta}_{jX}^{A}\mathbf{X}_{jnt} + \beta_{jAtt}^{A}Att_{n}^{A} + \mu_{jn}^{A} + \varepsilon_{jnt}^{A}\right) \end{aligned} \tag{1}$$

where $\mathbf{S}_n$ is a vector of individual background characteristics, $\mathbf{X}_{jnt}$ is a vector of vehicle attributes (including charging options for EV, and interactions with background characteristics), Att_{n}^{w} is a latent variable, $\boldsymbol{\beta}_{jS}^{w}, \boldsymbol{\beta}_{jX}^{w}$ and β_{jAtt}^{w} are vectors of coefficients associated with the variables and ASC_{j}^{w} are the typical alternative-specific constants. The μ_{jn}^{w}'s are error components, normally distributed (with mean zero and standard deviation σ_{μ}^{w}) across individuals. Finally, the ε_{jnt}^{w}'s are random terms distributed identical and independently extreme value type 1 (i.i.d. EV1) for each wave, while $\theta=\sigma^{A}/\sigma^{B}$ is a scale parameter that is equal to the ratio of the standard deviations of ε_{jnt}^{w}. This causes the error variances in the two dataset to be equal, allowing us to merge the two datasets and estimate a joint model.

The vehicle attributes do not change before and after, because individuals are presented with the same SC design. However, their coefficients are allowed to vary, to test if the real life experience modifies preferences for characteristics of EVs. In our model we also test whether individual attitudes as well as their effect on the

[1] New vehicle technologies often use electric motors together with other types of propulsion e.g.. hydrogen, gasoline/battery hybrids. We focus on pure battery electric propelled vehicles.

discrete choice change due to the experience with the EV. Hence both the latent variables (Att_n^w) and their coefficients (β_{jAtt}^w) in the model may differ between the before and after experiment.

Following the framework of hybrid choice models (Walker, 2001; Ben-Akiva et al., 2002; Ortúzar and Willumsen, 2011), we model the environmental attitude in each wave w as a latent variable that depends on the background characteristics ($\mathbf{S}_n^{'}$) of each individual n:

$$Att_n^w = \kappa^w + \boldsymbol{\lambda}^w \mathbf{S}_n^{'} + \omega_n^w \tag{2}$$

where κ^w is the intersect, $\boldsymbol{\lambda}^w$ is the vector of coefficients associated with the background characteristics ($\mathbf{S}_n^{'}$) and ω_n^w is the error term, normally distributed with zero mean and standard deviation σ_μ^w. $\mathbf{S}_n^{'}$ can be different from the background characteristics included in the discrete choice model reported in equation (1) and all coefficients are allowed to vary between the waves.

For each individual n, R statements associated with the attitude of environmental concern are used as indicators I_{rn}. These are associated to the latent variable (Att_n^w) with the following equations (called *measurement equations*):

$$I_{rn}^w = \gamma_r^w + \alpha_r^w Att_n^w + \upsilon_{rn}^w \qquad r = 1,...,R \tag{3}$$

where γ_r^w is the intersect, α_r^w is the coefficient associated to the latent variable (γ_1^w and α_1^w , i.e. the coefficients of the first indicator in both waves are normalised to zero and one, for identification purposes), and υ_{rn}^w are normally distributed error terms with zero mean and standard deviation σ_ν^w. All coefficients in equation (3) are also allowed to vary between the before and after experiment.

The hybrid choice model is then defined as follows. In each wave, the probability that individual n chooses alternative j in choice task t conditional on ω_n and μ_n is given by the typical multinomial logit model (MNL), where C_n is the set of alternatives available to each individual n:

$$\begin{aligned} P_{jnt}^B\left(\mu_{jn}^B, \omega_n^B\right) &= \frac{\exp(ASC_j^B + \boldsymbol{\beta}_S^B \mathbf{S}_n + \boldsymbol{\beta}_X^B \mathbf{X}_{jnt} + \beta_{Att}^B Att_n^B(\omega_n^B) + \mu_{jn}^B)}{\sum_{j \in C_n} \exp(ASC_j^B + \boldsymbol{\beta}_S^B \mathbf{S}_n + \boldsymbol{\beta}_X^B \mathbf{X}_{jnt} + \beta_{Att}^B Att_n^B(\omega_n^B) + \mu_{jn}^B)} \\ P_{jnt}^A\left(\mu_{jn}^A, \omega_n^A\right) &= \frac{\exp(\theta(ASC_j^A + \boldsymbol{\beta}_S^A \mathbf{S}_n + \boldsymbol{\beta}_X^A \mathbf{X}_{jnt} + \beta_{Att}^A Att_n^A(\omega_n^A) + \mu_{jn}^A))}{\sum_{j \in C_n} \exp(\theta(ASC_j^A + \boldsymbol{\beta}_S^A \mathbf{S}_n + \boldsymbol{\beta}_X^A \mathbf{X}_{jnt} + \beta_{Att}^A Att_n^A(\omega_n^A) + \mu_{jn}^A))} \end{aligned} \tag{4}$$

We assume that choices are correlated across choice tasks within each period but independent across time periods (before and after). So we need to compute for each period w, the probability of individual n making the sequence of choices $\mathbf{j} = \{j_1,...j_T\}$, which is the product of the probabilities in equation (4) over the T choice tasks. The unconditional probability is then the integral over the distribution of ω_n and μ_n:

$$P_{\mathbf{j}n}^{w} = \int_{\omega,\mu} \prod_t P_{jnt}^{w}(\mu_n,\omega_n) f_{Att}^{w}(\omega_n) \prod_r f_{Ir}^{w}(I_{rn} \mid Att_n^{w}(\omega_n))\, f(\mu) f(\omega)\, d\mu d\omega \tag{5}$$

where $f_{Att}(\omega_n^w)$ and $f_{Ir}(I_{rn}^w \mid Att_n^w(\omega_n^w))$ define the distributions of the latent variable and the indicators, respectively.

The joint hybrid choice model was estimated using Maximum Simulated Likelihood coded in *PythonBiogeme* (Bierlaire and Fetiarison, 2009).

3 DATA COLLECTION

To measure the extent to which real experience with EVs may affect preferences and attitudes, a panel dataset was gathered before and after individuals tested an EV. Since there are very few EVs on the market yet, data was collected using a SC experiment. The panel survey was structured in two waves with a three month period in-between:

- In the first wave, participants were asked to complete an internet survey, consisting of background information, a customised SC experiment and a set of attitudinal questions.
- After the first wave, respondents received an EV, which they could use for three months as if it was their own.[2]
- The second wave of data collection started after the three-month period. Respondents were asked to redo the survey that they had completed in the first wave.

A stand-alone web survey application was developed specifically to collect the relevant data for the analysis (Jensen *et al.*, 2012). The sample consists of individuals who participated in a real life experiment with EVs. They were randomly selected among more than 10,000 households that applied voluntarily in response to an advertisement sent out in the local press. To be selected, respondents needed to fulfil a few criteria pertaining to their electric installations at home and access to a private parking space, which was needed to install a designated charging device. The target in our sample was households who had bought a car within the last 5 years or intended to buy a car within the next five-years. Indeed, five years are a long time, but a car purchase is an important decision that usually requires long time to be finalised. The various factors considered in the decision are usually remembered long time after the purchase. Furthermore consumers usually start thinking of what type of car they would like to buy in advance of the actually purchase.

The survey included two SC experiments for each respondent – one each before and after the EV experience. The experiment in each wave consisted of binary choices between a conventional vehicle (ICV) - gasoline or diesel - and an EV. The attributes describing the cars included purchase price, driving costs represented by fuel costs, driving performance defined as top speed, and environmental performance described by carbon emissions. Particular attention was devoted to the attribute driving range.

In contrast to other studies, the experiment also included attributes regarding charging possibilities and battery lifetime for the EV. As an introduction to the SC experiment, each respondent was given information

[2] Except for a few Citroën C1 EVIE, the vehicles used in the three-month EV trial were, the Mitsubishi ImiEV, Citroën C-Zero and Peugeot I-on. These were among the first EVs available on the Danish market.

about the choice scenarios and a brief general description about EVs, recharging types, and environmental impacts. Thus, even in the first survey before a respondent obtained experience with an EV in their daily life, respondents possessed a minimum knowledge of the alternatives that they were asked to evaluate.

The SC scenarios were customised to each respondent to make them as relevant and realistic as possible. In particular, respondents were first asked to state the last vehicle they had purchased within the past five years. If no purchase had been made, an anticipated purchase within the next five years was used. Individuals who declared no recent or intended future purchase were asked to imagine they had to purchase a car and to indicate the preferred car class and condition. Although these individuals are not in our target we decided to interview them and then to control for purchase price and the average preference for this specific segment. As shown in Table 1, this segment counts only 28 individuals. Hence 92% of our sample is composed by households who bought a car recently or plan to buy an additional car. All but five households possess a car, 51% have only one car while 49% have two or more, while in 2012, 60% of Danish households owned a car; 76% of these have one car, while 24% had two or more[3].

Table 1: Descriptive statistics for the dimensions of the reference purchase

Variable	Category	Frequency	Percent
Purchase situation	Did purchase within the last five years	206	55.8
	No recent or future car purchase	28	7.6
	Will purchase an extra car in the next five years	7	1.9
	Will replace a current car in the next five years	128	34.7
Car class	Mini	36	9.8
	Small	81	22.0
	Medium 1	101	27.4
	Medium 2	93	25.2
	Large	7	1.9
	MPV	41	11.1
	Other	10	2.7
Car condition	New	114	30.9
	Used 0 - 5 years old	163	44.2
	Used 5 - 10 years old	92	24.9

Respondents could choose among a predefined set of seven car classes: Mini, Small, Medium 1, Medium 2, Large, Multiple Purpose Vehicles (MPV) and a final class called "other" if none of the previous six car classes fully described the relevant car class. Pictures and a brief description of the cars belonging to each class were provided to help respondents identify the class of reference for their choice experiments. It was possible to choose whether the (past or future) car purchase was or would be a new car, a used 0-5 years old car or a used 5-10 years old car and whether the propulsion would most probably be gasoline or diesel. The reference values for the attributes were based on average values of car models sold in Denmark and on a number of considerations regarding electricity consumption for the EVs and emissions from the electricity production. Briefly to give an idea, for a new gasoline car, the reference propulsion cost is €0.0733/km for the class Mini, and €0.1053/km for the class Medium 1. The corresponding values for the EV alternative are

[3] Klöckner et al. (2013) suggest that more multicar households are possibly in the sample because this segment has a higher interest in EVs.

€0.0267km and €0.04/km (for more details see Jensen, 2010). Table 1 shows the details of the reference purchase for the sample, i.e. the purchase indicated by the individuals interviewed.

The scenarios were generated by pivoting around the attribute reference values according to an orthogonal design. All attributes were treated as alternative specific and varied among 4 levels, except for the possibility of charging at work where it was only either "possible" or "not possible". The final design matrix consisted of 64 scenarios derived from a $4^{14}2^{1}8^{1}$ orthogonal main-effects design. A variable with eight levels was used to create eight blocks to divide the 64 scenarios among respondents[4].

Information about attitudes was collected by means of 27 attitudinal statements covering topics assumed relevant for the choice of an EV. For each statement the respondent could answer on a five-point category scale. The level of agreement to each statement then served as perceptual indicator variables[5]. One example of a statement used in our work is "I am completely convinced that global climate changes caused by human activities are taking place" and it was possible to answer from "strongly agree" to "strongly disagree". A factorial analysis on the responses allowed identification of three main attitudes to be investigated; environmental concern, technology interest, and perception of the car as a status symbol.

Hybrid choice models are complicated and difficulties increase with the number of latent variables. Here we have two latent constructs for each latent variable as there is one for each wave. Therefore we focus on the most important latent effect; there are R = 7 indicators linked to the latent variable, environmental concern.

After a check of the data, to ensure that the same respondent answered in both waves, i.e. completed all choice experiments and attitudinal statements, the dataset with complete answers included 369 individuals. Since each individual answered eight choice tasks in each wave (before and after they experienced an EV in their daily life), the final dataset available for the estimation consists of 5904 SC observations.

4 MODEL RESULTS

We tested various hybrid choice models and the results from the best model are summarised in Tables 2-4. The model includes linear effects, non-linear effects, systematic heterogeneities in the preference for vehicle attributes and in the specific preference for the EV alternative, latent effects for environmental concern, and within-wave correlation across the SC observations from each individual. All coefficients that were not significantly different (at least at 80%) between the two waves were constrained to be generic, and are reported in the first column in Table 2. The coefficients that were different at least at 80% were left specific for each wave, i.e. before and after the real experience. The coefficients estimated specific for each wave are reported respectively in the second and third column. The first part of Table 2 reports the results of the discrete choice model, while the second part reports the results of the latent variable model and the loglikelihood (LL) of the hybrid joint model that corresponds to the global function and not to the choice model alone.

Table 3 reports the market share elasticities for EV and ICV with respect to all the car characteristics tested in our model. Individual elasticities were simulated using Monte Carlo simulation. Simulation is necessary, due to the fact that the mixed logit probability is the MNL probability conditional on the random coefficient. Since the elasticity includes both the probability and its derivative, we need simulation to compute the unconditional elasticity, i.e. the average elasticity over the population. For the dummy variables, we used the relative change of expected aggregate shares from an increase of the value of the variable from 0 to 1, as

[4] The experimental design was developed using SAS macros for designing discrete choice experiments (Kuhfeld, 2009).
[5] Statements were defined based on Mokhtarian et al. (2001), Vredin Johansson et al. (2006), Bolduc et al (2007) and Atasoy et al. (2010).

described in Bhat and Pulugurta (1998). For variables with piecewise linear specification we computed the aggregated elasticities for one value in each interval. The values reported in the tables are average values computed using sample enumeration (i.e. they are computed for each individual and then averaged over the sample). The SC elasticities are not to be interpreted in absolute sense but only compared relatively, because SC data are not real data.

Table 4 reports the willingness to pay (WTP) computed with respect to the purchase price. The WTP measures are calculated for a new small car class purchase. Simulation is not required to compute WTP. The values reported in the tables are computed using sample enumeration. Moreover, we assumed that observations are independent as if they belong to different individuals, because it does not make sense to account for panel correlation among SC data in prediction. The confidence interval of the WTP is computed using the method illustrated in Armstrong et al. (2001). These confidence intervals are generally not symmetric, and in fact, also in our case, the upper bound is usually larger, though not dramatically.

In the estimation results, all the coefficients have the expected sign. In particular, purchase price, fuel costs, and carbon emissions are negative. The other coefficients, which describe car performance (such as top speed, driving distance) and charging options, are positive. We also tested that all the marginal utilities, accounting for all the systematic heterogeneity, have the correct sign. In addition, the results show that the scale parameter (θ) that allows for heteroscedasticity between waves is not significantly different from one (the hypothesis H0: $\theta=1$ is rejected at the 67 % level in a two-tailed test), confirming that the two data sets have the same variance. The standard deviation (σ_μ) that accounts for a panel effect is significant for both data sets, as expected.

Furthermore, almost half of the coefficients in our model are significantly different between waves, showing that individual preferences are indeed affected by the real experience. It seems that EV experience also makes individuals re-evaluate the characteristics of the ICV, not only the preferences of the EV characteristics.

Among all the attributes, driving range is one of the most critical factors for the EVs. In line with the discussion in Dimitropoulos et al. (2012), we tested several non-linear specifications, including logarithm and power functions. We found that the linear utility with coefficients specific for EV and ICV was the best. However we found that the marginal utility of one extra kilometre is clearly much higher for the EV than for the ICV. Since the driving range is much smaller for the EV than for the ICV, this difference might indicate presence of non-linear effects in the marginal utility. It is important to interpret this as a non-linear effect and not an effect of EV or ICV as these labels should not affect the respondents' preferences for driving range everything else equal. Our specification is like a piecewise linear function with two intervals, where the first interval is covered only in the EV utility and the second only in the ICV utility.

Table 2: Model estimation results

	Generic		Specific for each wave			
	Before/After		Before		After	
DISCRETE CHOICE MODEL	Value	t-test	Value	t-test	Value	t-test
Linear Effects						
Alternative specific constant (ASC_{EV})			-0.32	-0.47	-2.7	-3.4
Standard deviation for panel effect, ($\sigma_{\square}$)			1.13	8.25	-1.46	-8.83
Purchase price [*100.000DKK*]	-0.59	-7.24				
Fuel costs (EV) [*DKK/km*]	-2.42	-4.73				
Fuel costs (GAS) [*DKK/km*]			-0.95	-3.12	-1.69	-4.66
Driving range (EV) [*100km*]			0.78	4.28	1.62	6.61
Driving range (GAS) [*100km*]	0.04	2.07				
Carbon emissions [*100g/km*]	-0.55	-5.06				
Topspeed (0-120km/h) [*100km/h*]			2.81	2.24	5.24	3.9
Topspeed (120-160km/h) [*100km/h*]			1.17	3.59	0.06	0.15
Topspeed(over 160km/h) [100km/h]	0.07	0.37				
Battery stations [*100*]	2.72	6.09				
Battery life [*100.000km*]			0.35	4.26	0.54	4.93
Charging at workplace [*dummy*]	0.25	2.67				
Charging in city centres and train stations [*dummy*]			0.55	4.77	0.34	2.49
Charging in city centres [*dummy*]	0.46	4.87				
Charging at larger train stations [*dummy*]	0.33	3.51				
Systematic heterogeneity in the attributes						
Purchase price No car purchase	0.54	3.21				
Car purchase is a used car	-0.4	-3.63				
Car purchase is Mini class			-1.81	-3.19	-3.16	-3.39
Car purchase is Small class	-1.02	-4.86				
Car purchase is Medium 1 class	-0.50	-4.03				
Driving range Car purchase is 2^{nd} car (EV)			-0.22	-0.96	-0.6	-2.55
Battery stations Car purchase is 2^{nd} car (EV)			-1.81	-2.64	0.05	0.07
Charging at workplace work distance > 10km (EV)	0.4	2.89				
Systematic heterogeneity in the EV alternative						
Car purchase is Mini class (EV)	1.42	4.87				
Car purchase is Small class (EV)	0.86	3.51				
Car purchase is Medium 1 class (EV)			0.48	2.02	-0.01	-0.02
Car purchase is 2^{nd} car (EV)	0.90	2.35				
Car purchase is a used car (0-5 years old) (EV)	0.47	2.57				
Car purchase is a used car (5-10 years old) (EV)	0.99	4.73				
Male (EV)	-0.48	-3.15				
Latent Environmental attitude (β_{jAtt})	1.86	5.12				
Scale between waves (θ)					0.91	0.99[a]

[a] p-value for the t-test against 1

Table 2: Model estimation results (*continued*)

	Generic		Specific for each wave			
	Before/After		Before		After	
LATENT VARIABLE MODEL	Value	t-test	Value	t-test	Value	t-test
Structural model						
Intersect (κ)			1.32	10.35	1.41	11.01
Standard deviation of error term ($\sigma_{\square}$)			-1.38	-15.3	-1.22	-14.75
Age of respondent is 26-35 years	0.15	1.37				
Age of respondent is 36-45 years	0.19	1.70				
Age of respondent is 46-55 years	0.17	1.57				
Age of respondent is 56-65 years	0.26	2.21				
Age of respondent is over 65 years	0.29	2.18				
Car purchase is Mini class	-0.14	-2.45				
Number of cars in household	0.13	4.10				
Measurement equation						
Indicator (r=1): standard deviation (σ_1)	-0.56	-20.22				
Indicator (r=2): intercept (γ_2)	0.77	3.43				
attitude (α_2)	1.17	9.42				
standard deviation (σ_2)	0.09	4.21				
Indicator (r=3): intercept (γ_3)	-0.97	-3.49				
attitude (α_3)	1.53	9.19				
standard deviation (σ_3)	-0.23	-5.98				
Indicator (r=4): intercept (γ_4)			-0.97	-3.78	-1.49	-4.80
attitude (α_4)			1.46	9.33	1.79	9.63
standard deviation (σ_4)			-0.52	-8.92	-0.28	-5.17
Indicator (r=5): intercept (γ_5)	-0.80	-4.04				
attitude (α_5)	1.44	12.05				
standard deviation (σ_5)	-0.37	-11.23				
Indicator (r=6): intercept (γ_6)	0.10	0.43				
attitude (α_6)	1.34	10.18				
standard deviation (σ_6)	-0.18	-6.83				
Indicator (r=7): intercept (γ_7)	-0.61	-2.67				
attitude (α_7)	1.45	10.44				
standard deviation (σ_7)	-0.22	-6.54				

SUMMARY STATISTICS	
Number of observations	5904
Number of individuals	369
Number of estimated parameters	79
Log-likelihood at the maximum (choice model)	-3124
Log-likelihood null (choice model)	-4092
$\bar{\rho}^2$	0.223

In our experiment, the importance attached to driving range for the EV almost doubles after individuals have tried the car, which means that individual concern was confirmed by the characteristics of the EVs currently in the market. As expected, this effect is much less prominent in multi car households[6], because they can rely on the other car (that is an ICV) if need arises for longer trips. Clearly, driving range plays a key role in the demand for EV; the direct elasticity for EV with respect to driving range in fact doubles after the experience for both single and multi car households. The same effect can be found in the WTP for driving range. The 95% WTP confidence intervals before and after the experience only has a minor overlap for single car owners, indicating that the EV experience indeed changes the WTP even after accounting for the dispersion around the point estimates. In a meta-study focusing specifically on driving range, Dimitropoulos et al. (2012) found that on average, consumers are willing to pay between €52 and €58 for a one kilometre increase in driving range. These WTPs are in line with the point estimate we obtained before the EV experience, but they barely follow within the confidence intervals after the EV experience.

Table 3: Direct and cross elasticity for EV and ICV (sample average for the sample)

	Demand elasticities for EV		Demand Elasticities for ICV	
	Before	After	Before	After
Purchase price EV	-1.22	-1.35	0.93	0.76
Purchase price GAS	1.13	1.27	-1.02	-0.83
Fuel costs EV	-0.36	-0.37	0.30	0.23
Fuel costs GAS	0.32	0.59	-0.30	-0.41
Driving range EV (for single car household)	0.66	1.34	-0.58	-1.02
Driving range EV (for multiple car household)	0.44	0.91	-0.46	-0.57
Driving range GAS	-0.15	-0.16	0.14	0.10
Carbon emissions EV	-0.20	-0.21	0.17	0.13
Carbon emissions GAS	0.36	0.38	-0.33	-0.25
Top speed EV (evaluated at 100km/h)	1.46	2.88	-1.34	-1.88
Top speed GAS (evaluated at100km/h)	-1.46	-2.88	1.34	1.88
Top speed EV (evaluated at 140km/h)	0.85	0.04	-0.78	-0.03
Top speed GAS (evaluated at 140km/h)	-0.85	-0.04	0.78	0.03
Top speed EV (evaluated at 180km/h)	0.06	0.06	-0.06	-0.04
Top speed GAS (evaluated at 180km/h)	-0.06	-0.06	0.06	0.04
Battery life	0.31	0.51	-0.30	-0.35
Battery stations (for single car households)	0.21	0.21	-0.20	-0.16
Battery stations (for multiple car households)	0.07	0.22	-0.07	-0.15
Charging at work (for work distance <= 10km)	0.12	0.11	-0.09	-0.06
Charging at work (for work distance > 10km)	0.30	0.31	-0.22	-0.16
Charging at larger train stations	0.14	0.15	-0.12	-0.09
Charging in city centres	0.20	0.21	-0.16	-0.12
Charging at city centres and larger train stations	0.25	0.15	-0.19	-0.09

Top speed is another attribute that varies significantly before and after individuals have tried an EV. We tried several non-linear specifications for top speed and we found that the piecewise linear utility function gave the best results. As expected, the marginal utility is higher for top speeds lower than 120km/h and, similar to the result for driving range, it increases twice as much after experience with the EV. In line with these results

[6] Multi car households are households that have more than one car or households declaring in the survey that they intend to purchase a second car.

the average WTP for top speeds lower than 120km/h almost doubles after trying the EV. However, the confidence intervals are quite large and significantly overlap before and after. Clearly, top speeds below 120 km/h are not acceptable and have a significant impact on the demand for EV. The elasticity with respect to top speed lower than 120km/h is the highest among the attributes we tested. While Dagsvik et al. (2002) computed the WTP for age and gender segments, and found that the value ranges between €14 and €70 and Batley et al. (2004) reports an average value of €46km/h, these values cannot be directly comparable, because they both use linear specifications. We also tested a linear specification for top speed and obtained WTP in line with those studies: €38km/h, for a new, mini car class purchase, €85km/h for medium 2 class, and €140km/hr for the largest car class segments. Since the piecewise linear specification is superior to the linear, this confirms that the difference in our study and others is not due to differences in the context but to significant non-linear effects in the perception of top speed.

The other variables where the effect also changes after the experience with the EV are fuel cost, battery life and charging in city centres and train stations. Regarding fuel cost we found a factor of 2.5 between the EV and ICV coefficients. A similar result was found in Glerum et al. (2011), where the ratio between the two coefficients was found to be 2.25. The EV coefficient is stable between waves, whereas the ICV fuel cost coefficient becomes more negative after the experience and closer to the preference for the EV electricity.

Regarding the effect of the reference purchase we found that the car class has a direct effect on the alternative chosen as well as on how important the purchase price is for the choice. As expected the preference for EVs is higher for smaller car classes than for larger car classes. However, other than that we also found that marginal utility of purchase price is higher for respondents who chose a smaller car class than for those who chose a larger car class. Since the purchase price increases across car classes, the effect on the marginal utility of the purchase price can reveal an income effect. We then performed several tests to investigate for the presence of income effects in our sample. Following Jara-Diaz and Videla (1989), we test a quadratic transformation of the purchase price. We find that the squared price was significant and positive (hinting to the presence of an income effect), but only if we left out the interaction between car classes and purchase price. When we included this latter interaction, the squared price lost significance. We also tested whether the marginal utility of purchase price varied with individual income by estimating a price coefficient for respondents with gross monthly household income over €6,600, as in Mabit and Fosgerau (2011), but this was not significant. It thus appears that the effect of the car classes on the marginal utility of the purchase price is not capturing an income effect.

Finally, the positive value for the coefficient of the latent environmental attitude indicates that people with higher environmental concern have a greater preference for EVs. Furthermore, the effect of the environmental concern in the overall utility of EVs is not affected by the EV experience. In the estimation results we report a generic coefficient. Before, however, constraining the latent environmental attitude coefficients to be generic between the waves, the point estimated values of the latent environmental attitude before and after the EV experience was quite different and highly significant in both cases, but they were not significantly different from each other. Furthermore, as the coefficients in the latent variable model were specified specific for each wave, we were able to take into account if the attitude itself changed between the waves. As we did with the discrete choice model, we estimate a model with wave-specific coefficients and then use the robust t-test to test for correlation. As shown in the second part of Table 2, we restrict most of the coefficients finding that the attitude itself does not change between waves.

Table 4: Willingness to pay (evaluated for new car purchase, small car class)

	Sample average point estimates and 95% confidence intervals of the WTP distribution						
	Before			After			
	Lower limit	Point est.	Upper limit	Lower limit	Point est.	Upper limit	Unit
Fuel costs EV	115	200	310	115	200	310	€/(€cent/Km)
Fuel costs GAS	29	79	140	80	140	215	€/(€cent/Km)
Driving range EV (for single car household)	34	65	104	91	134	193	€/Km
Driving range EV (for multiple car household)	16	46	82	48	84	130	€/Km
Driving range GAS	0.2	3.3	6.8	0.2	3.3	6.8	€/Km
Carbon emissions	27	46	69	27	46	69	€/(g/Km)
Top speed (evaluated at 100km/h)	29	233	466	214	434	703	€/(Km/h)
Top speed (evaluated at 140km/h)	43	97	163	-62	5	72	€/(Km/h)
Top speed (evaluated at 180km/h)	-26	6	38	-26	6	38	€/(Km/h)
Battery life	15	29	46	27	45	68	€/1000km
Battery stations (for single car households)	148	225	328	148	225	328	€/Unit
Battery stations (for multiple car households)	-12	75	166	129	229	354	€/Unit
Charging at work (for work distance <= 10km)	123	2070	3893	123	2070	3893	€/Unit
Charging at work (for work distance > 10km)	3482	5383	8039	3482	5383	8039	€/Unit
Charging at larger train stations	1202	2733	4574	1202	2733	4574	€/Unit
Charging in city centres	2214	3810	5873	2214	3810	5873	€/Unit
Charging at city centres and larger train stations	2603	4555	7085	600	2816	5375	€/Unit

5 CONCLUSION

We have examined the effect that hands-on experience with an EV has on the preferences and attitudes towards EVs and ICVs. We use data collected in two waves, before and after the respondents had a three-month real experience with an EV. Our results show that individual preferences do change after the use of an EV in real life. In particular our results confirm that driving range is a major concern related to EVs but also reveal that the concerns that individuals have about low driving ranges are not due to misconceptions, but a true mismatch between the range they wish to have available in their everyday lives and what the EVs provide.

Our results also show that top speeds below 120km/h are not acceptable. This result is promising because most of the recently produced EVs have top speeds over120km/h. This was not the case some years ago, and especially at the beginning, respondents were given early market EVs with low top speeds. We found that the possibility to charge at work, the number of battery stations in the road network and general charging locations in the public space are important attributes when studying the demand of EVs.

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Exploring different sources of variation in individual preferences for Electric Vehicles

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ABSTRACT

In this paper we explored different sources of variation in preferences for electric vehicles (EVs) and the extent to which these are affected by real-life experience with an Electric Vehicle (EV). In particular we investigated the effect of knowing that one has been selected for an EV demonstration project, the effect of scale among datasets and the effect of scepticism. We used data collected before and after individuals tried an EV, in real life, for a period of three months; this includes a set of attitudinal data and a set of experimental choices between an EV, a conventional vehicle and a no-choice option. We found that with more experience, only preferences for the EV alternative changed and, in particular, the preferences for driving range and conventional charging in city centres increased significantly. When testing whether there is a difference between those who knew they were selected to participate in an EV demonstration project and those who did not, we found that the former showed stronger sensitivity to fuel costs and number of battery stations. In general we did not find any scale differences between the before and after data, nor a reason to parameterise the scale parameter. Finally, we found that individuals who are more sceptic (conservative) showed lower preferences for the EV before the experience, whereas this effect was not significant after the experience.

1 INTRODUCTION

The increased focus on electric vehicles (EVs) as an alternative to conventional gasoline and diesel cars has led to several studies on this topic. An established way to model the importance of different characteristics of an alternative for different segments of the population is to estimate discrete choice models on data collected with stated preference (SP) data. Furthermore, a few studies have included attitudes specifically in the choice model. However, in such hypothetical settings, individuals are asked to indicate their intentions or preferences before these have necessarily been constructed. As very few consumers have experience with EVs so far, demonstration projects have previously been used to give consumers experience with EVs, but the methodology used has not allowed for measuring the marginal valuation of EV specific attributes. In connection with a Danish demonstration project (Test-en-Elbil), where a number of households were offered an EV for three months, we collected choice and attitudinal data before and after individuals had experienced the EV in real life. We used two different survey applications. In the first application (pilot survey), the choice experiment was built using an orthogonal design, while the second application (final survey) was built using an efficient design (Rose & Bliemer 2009). In particular, we used the results from the pilot survey to build the final survey, so both surveys are similar, but there are some differences in the attributes of the choice experiment, the background variables and the attitudinal statements. In Jensen et al. (2013), we investigated differences in preferences and attitudes before and after the experience using the pilot survey data, as we realised that we had a large quality dataset worth analysing. The final survey was then described in detail in Jensen et al. (2014), together with analyses of the collected data, but so far we have not presented any model estimations. The similar configuration of the two surveys allows us to test the reliability of the estimated results by comparing similar models estimated on both datasets. Furthermore, as the final survey includes some attributes and features that were not included in the pilot application, this allows us to extend the analysis conducted by Jensen et al. (2013) in several directions. First and foremost, the purpose of this paper is to explore the change in preferences and attitudes before and after experience with EVs and how these changes affect the choice of the EV alternative. In particular, we discuss and test the following aspects: (1) the effect of the scale parameterisation; (2) the effect of knowledge of having been selected; (3) the effect of a latent variable, called scepticism; (4) a comparison between the results obtained with the orthogonal and the efficient designs.

The individuals chosen for the demonstration project were selected randomly among those who signed up for the project. Beside the 290 individuals who answered both waves of the survey, a large number of individuals who signed up for the demonstration project, but were not yet selected to participate, answered wave 1 of the survey. One thing we would like to investigate is whether there was a difference in the preferences for the car attributes of those who were chosen to participate (and were aware of this) and those who were not. The problem is linked to the issue of self-selection bias (Wooldridge 2010) as respondents may (wrongly) assume that if they indicate more positive preferences or attitudes towards EVs, then they might have a higher probability of being chosen.

The decision to study the effect of scepticism is motivated by the results obtained by Jensen et al. (2014). The scepticism attitude is defined by latent constructs (attitudinal statements) regarding the usefulness of EVs and new technology in general. In that paper we find that there are significant differences in the response to the corresponding indicator statements across the data collected before and after the EV experience. Therefore, we decided to investigate the effect of scepticism in greater depth. Moreover, as far as we are aware, it has not been investigated in previous studies about EVs.

While great effort is often put into explaining behaviour using models that recognize systematic or stochastic variations across individuals, less effort has been put into studying heterogeneity in the error structure (Swait & Bernardino 2000). In the model presented in Jensen et al. (2013), we accounted for differences in the mean of the scale across the datasets collected before and after experiencing and EV but did not find a significant difference. In this paper, we investigate whether there is a variation around the mean due to differences in background characteristics and how much the EV was used during the trial period.

There is an interesting discussion in the field about the effect of using orthogonal versus efficient designs. While the advantages in terms of efficiency are well demonstrated (Rose & Bliemer 2009), it is still debated whether these advantages are obtained at the cost of robustness. This comparison was not our specific goal when we built the survey. However, since we have very good and comparable data with both types of experiments, we think that a comparison can add some evidence to this discussion. To compare the data collected with the orthogonal design and the efficient design directly, we estimated a model based on data from the final survey that is as similar as possible to the model estimated by Jensen et al. (2013).

The rest of the paper is organised as follows. Section 2 briefly describes the data used in this paper. Section 3 first presents the best model specification with the data collected in the final survey and then discusses the different sources of variation in preferences that we investigated. Finally, our conclusions are presented in Section 4.

2 DATA

The data used in this paper comes from a two-wave SP experiment including attitudinal questions that was applied before and after respondents had experienced an EV in real life for a three-month period. Respondents applied voluntarily on the home page of the demonstration project and were chosen based on a few criteria, where the most important one was that there should be at least one car available in the household. Households would have the EV for three months and then the vehicle would be moved to another household. After respondents applied, they would have the chance of being chosen every time an EV in the municipality where they lived finished the three-month period with another household. The sample is described in more detail in Jensen et al. (2014). The survey was structured in two steps: First, a large pilot data collection was conducted between January 2011 and June 2012 using a SP experiment on the choice between an EV and a conventional vehicle (ICV) built using an orthogonal design. Then, based on the results from the pilot, another SP experiment was built using an efficient design. The latter was used in the final survey. The survey methodology is described in detail in Jensen et al. (2014). Besides a few changes in the attribute values, the main difference in the experiment was that it incorporated a no-choice alternative, which respondents could choose if neither the EV nor the ICV alternative was found desirable. Adding a no-choice alternative is not new. It has been argued that if individuals are forced to choose among undesirable alternatives gives rise to inappropriate model selection, biased welfare estimates and poorer fit in statistical models (Olsen and Swait, 1995; Scarpa et al. 2007). Furthermore, some attitudinal questions were changed, so that they covered specific EV related topics. An overview of the difference between the two surveys is shown in Table .

Table 1: Overview of the two surveys

	Pilot survey	Final survey
Purchase price	X	X
Fuel costs	X	X
Carbon dioxide emissions	X	X
Driving range	X	X
Battery lifetime	X	
Number of battery stations	X	X
Top speed	X	
Charging at work	X	
Public charging	Charging in city centres	Conventional charging in city centres
	Charging at train stations	Quick charging in city centres
	Charging in city centres and at train stations	Conventional charging at shopping centres
		Quick charging at shopping centres
Alternatives	Electric car	Electric car
	Conventional car	Conventional car
		No choice
Design method	Orthogonal design	Efficient design
Attitudinal questions	Concern about climate changes	Concern about climate changes and pollution
	Technology	Technology
	Car performance	Car performance
		EV performance
		EV usage (mobility)

Another difference between both datasets is that everybody who applied for the demonstration project were invited to answer the pilot survey, but only the few selected to receive the car were asked to answer the same survey after the three months they had the EV at their disposal. Applicants for the demonstration project were not invited to fill in the questionnaire until they were informed that they had been chosen to participate. This was the method used in the pilot and in the final survey. However, when there was still one year left of the demonstration project, the number of applicants was very high (more than 25,000) and we decided to invite everybody who applied to answer the final survey. If they answered it before they were chosen, they still had the chance of being chosen at a later stage (in which case they would answer the survey again). However, this was the case for only a few of the individuals and these are not included in the sample used in this paper. In the final dataset then, it is possible to identify three segments of respondents:

- Segment 1 includes people who were not chosen to participate in the demonstration project (i.e. did not receive an EV), so they only answered the final survey in the "first wave". These individuals did *not* know if they would be chosen later.
- Segment 2 includes people chosen to participate in the demonstration project who answered only the first wave (i.e. dropped from the survey after the first wave). Unfortunately, we could not investigate the reasons for them dropping out. These individuals knew that they were chosen when they answered wave 1.
- Segment 3 includes people who were chosen to participate in the demonstration project and answered both waves of the final survey. This segment is analogous to the one in the pilot survey. As with segment 2, these individuals knew that they were chosen when they answered wave 1.

The total number of individuals in both surveys (pilot and final) and in each segment of the final survey is presented in Table along with a comparison of their socioeconomic attributes with those of the Danish population (DK pop).

Table 2: Number of individuals in each segment across waves and background characteristics

	DK pop	Pilot	Final		
			Segment 1	Segment 2	Segment 3
Number of individuals		369	5110	389	290
Age	48.7	45.4	46.2	44.7	45.4
Respondent is male	0.49	0.53	0.70	0.57	0.53
Number of cars in household	0.76	1.52	1.45	1.62	1.56
Number of people in household	1.94	3.26	3.23	3.35	3.34
Share of households with children	0.37	0.61	0.66	0.71	0.76
Share of EV choices (before/after)		0.48 /0.40	0.45/-	0.32/-	0.31/0.17
Share of ICV choices (before/after)		0.52 /0.60	0.38/-	0.45/-	0.46/0.58
Share of no-choice (before/after)		-	0.17/-	0.23/-	0.23/0.24

As shown in Table , the individuals who answered the pilot and final surveys have more cars and live more often in households with children compared to the Danish population. This is mainly because the most important requirement for participation was that there should be at least one car available in the household. The reason that families with children are overrepresented is connected to the car ownership prerequisite. In Denmark, 83% of families with children have a car, whereas only 52% of families without children have a car. The characteristics of the respondents in segment 3 and in the pilot are very similar, as expected, as both samples refer to respondents who received the EV for three months and answered the full panel survey, both before and after having tried the vehicle. It is interesting to note that the inclusion of the no-choice alternative affects the distribution of the choices. For segment 1 it affects the ICV alternative more, while for segments 2 and 3 (those who were chosen for the demonstration project) the EV alternative is more affected.

3 MODEL ESTIMATION

Using the data collected in the final survey for segment 3, we first tested several specifications to find the best model to measure the effect of experience in the choice of EVs. At the same time, we also tried to include the same variables that we found significant in the pilot dataset. Although it is not the objective of this section to compare results obtained with both datasets, the model takes into account the correlation between observations from the same individual n in each wave $w = (B, A)$ (where B = before and A = After) and also the scale effect between the data collected before and after the experience. Since the data includes the no-choice option, the utility specification for each of the three alternatives (j = EV, ICV, no-choice) is specified for waves B and A as follows:

$$
\begin{aligned}
U_{nt,EV}^{B} &= \alpha_{EV}^{B} + \beta_{x,EV}^{\prime B} x_{nt,EV} + \sigma_{EV}^{B}\ \zeta_{\ 1\mathrm{n}} + \rho^{B}\zeta_{2n} + \varepsilon_{nt,EV}^{B} \\
U_{nt,ICV}^{B} &= \alpha_{ICV}^{B} + \beta_{x,ICV}^{\prime B} x_{nt,ICV} + \sigma_{ICV}^{B}\zeta_{2n} + \varepsilon_{nt,ICV}^{B} \\
U_{nt,0}^{B} &= \alpha_{0}^{B} + \varepsilon_{nt,0}^{B} \\
U_{nt,EV}^{A} &= \theta\left(\alpha_{EV}^{A} + \beta_{x,EV}^{\prime A} x_{nt,EV} + \sigma_{EV}^{A}\zeta_{3n} + \rho^{A}\zeta_{4n} + \varepsilon_{nt,EV}^{A}\right) \\
U_{nt,ICV}^{A} &= \theta\left(\alpha_{ICV}^{A} + \beta_{x,ICV}^{\prime A} x_{nt,ICV} + \sigma_{ICV}^{A}\zeta_{4n} + \varepsilon_{nt,ICV}^{B}\right) \\
U_{nt,0}^{A} &= \theta(\alpha_{0}^{B} + \varepsilon_{nt,0}^{B})
\end{aligned} \tag{1}
$$

where α_j^w are the alternative specific constants (restricted to 0 for the no choice altenative), x_{jnt}^{w} are vectors of attribute values and $\beta_{x,j}^{w}$ are the vectors of corresponding parameter values (where the parameter for purchase price is restricted across waves for identification); σ_j^w account for the panel effect for EV and ICV; ρ for the correlation between them and ζ_{Rn} (with R = 1,...,4) are vectors of identically and independently distributed standard normal random variables. Walker et al. (2007) show that with panel data, the variance of the panel effect for all three alternatives can be empirically identified and only the variance for the extreme value should be normalized. Moreover, they show that instead of estimating a panel effect for each of the three alternatives, the panel effect of two alternatives and the correlation between them can be estimated. This reduces the number of random coefficients and thus estimation time. Furthermore, this makes interpretation of the random effects easier, as the σ_j^w can be interpreted as the variation in the utility relative to the no-choice alternative.

The estimated parameters are presented in Table 3. The columns EV/ICV indicate if the parameter estimated for the EV alternative is significantly different (and at which level) from the corresponding parameter estimated for the ICV alternative. Furthermore, the columns B/A indicate if a parameter estimated in wave 2 is significantly different (and at which level) from the corresponding parameter estimated in wave 1. We only present the B/A test for the EV specific parameters as no ICV specific parameters were significantly different across waves. For this model and for all the models presented in this paper, an *A* indicates that the parameter is restricted between the EV and ICV alternatives and its value is reported only for the EV and a *W* indicates that a parameter is restricted between waves and its value is reported only for wave 1. Hence, *WA* indicates that parameters are restricted across alternatives and waves. As in all our models we restricted the purchase price across waves and alternatives for identification. In the first model specification (Table 3), we only restricted parameters across alternatives or waves if we found a very strong reason to do so, for example, if we did not find significant differences between them in the various specifications tested. However, as we would like to use this model as the base model for further investigations, we tried not to be unduly restrictive, because some effects might turn out to be significant if more advanced specifications are used.

Table 3: Effect of direct experience on the individual preference

	Before					After					
	EV		ICV			EV		ICV			
	Value	Robust t-test	Value	Robust t-test	EV/ ICV	Value	Robust t-test	Value	Robust t-test	EV/ ICV	B/ A E V
Linear effects											
Alternative specific constant (α)	6.00	4.07	6.54	3.32		3.12	1.90	9.46	5.33	**	*
Standard deviation for panel effect (σ)	1.53	8.00	3.55	9.66	**	2.08	7.93	3.52	6.87	**	**
Correlation between EV and ICV (ρ)	2.53	7.18				2.97	5.46				
Purchase Price (PP)	-1.76	-6.59	WA			WA		WA			
Fuel costs	-4.42	-3.41	-1.95	-3.89	*	-2.75	-1.54	-1.84	-3.48		
Driving range	1.31	3.52	0.15	1.78	**	3.27	5.79	0.12	1.35	**	**
Carbon dioxide emissions	-0.14	-0.81	A			-0.256	-1.28	A			
Battery stations	1.27	3.41				1.32	2.88				
Public charging, slow, shop	0.25	0.96				0.351	0.98				
Public charging, slow, city	-0.09	-0.36				0.74	2.03				*
Public charging, fast, shop	0.52	2.07				0.803	2.31				
Public charging, fast, city	0.50	1.88				0.755	1.92				
Systematic heterogeneity in the alternatives											
Multi car household	0.45	0.46	-0.58	-0.51	**	-1.06	-1.59	-0.813	-1.38		*
Respondent is male	0.22	0.38	0.75	1.15	*	1.17	2.26	1.16	2.39		
Ref. car class is Mini class	2.68	2.62	1.17	1.24	**	W		W			
Ref. car is Small class	-0.35	-0.27	-1.64	-1.21	**	1.24	1.27	-0.422	-0.47	**	*
Ref. car is Medium 1 class	0.01	0.01	-0.49	-0.4		-0.92	-1.00	-0.696	-0.86		
Main car is used for commuting	0.78	1.18	0.42	0.54		-1.47	-1.66	-0.396	-0.58	*	**
Main car is used for daily transport	-0.87	-0.78	0.47	0.36	**	-1.96	-2.48	-1.4	-2.00		
Main car is used to pull a trailer	-0.64	-1.07	-0.90	-1.26		W		W			
Ref. purchase is in 1 year	0.25	0.24	0.66	0.65		0.18	0.18	-0.259	-0.27		
Ref. purchase is in 2 years	-0.13	-0.10	0.07	0.06		1.39	1.12	0.717	0.66		
Ref. purchase is in 3 years	0.93	0.66	1.40	1.07		1.25	0.91	1.22	1.08		
Ref. purchase is in 4 years	0.97	0.55	0.64	0.37		0.95	0.75	0.657	0.59		
Ref. purchase is in 5 years or more	0.54	0.29	-0.19	-0.09		1.56	0.98	-1.07	-0.75	*	
Respondent lives in a city	-0.52	-0.71	-0.24	-0.26		-0.27	-0.45	-0.15	-0.24		
Type of home is country house	-1.67	-2.03	-1.23	-1.25		-1.50	-1.66	-1.09	-1.38		
Systematic heterogeneity in the attributes											
Battery stations * Multi car household	-0.74	-1.68				0.68	1.23				**
PP * no expected car purchase	-0.44	-2.07	A			-0.79	-2.82	A			
PP * Mini car class	-3.51	-7.07	WA			WA		WA			
PP * Small car class	-1.37	-4.17	WA			WA		WA			
PP * Medium 1 car class	-0.64	-3.29	WA			WA		WA			
PP * ref. purchase is in 1 year	0.56	2.29	WA			WA		WA			
PP * ref. purchase is in 2 years	0.36	1.29	WA			WA		WA			
PP * ref. purchase is in 3 years	0.426	1.42	WA			WA		WA			
PP * ref. purchase is in 4 years	0.657	1.96	WA			WA		WA			
PP * ref. purchase is in 5 years or more	0.744	1.89	1.09	2.23		0.12	0.26	1.05	2.26	*	
scale						0.92	0.74^{T}				
Number of obs/individuals **Number of parameters = 103** **Log Likelihood = -2393** **Null Log likelihood = -3823** **$\bar{\rho}^2$ = 0.347**	1740/290					1740/290					

*Significant at 80%, **significant at 95%, T: t-test against 1, A: Alternative specific, W: Wave specific

In this section we focus on the effects that can be measured exclusively with the final dataset. The final survey includes a number of new background variables that were not possible to test with the data from the pilot. One interesting question, which was introduced in the final survey, referred to the usage of the cars available in the household (i.e. for which activity the car was mainly used). If the main car was used for commuting, then the preference for EV was significantly lower in wave 2 than in wave 1. If the main car was used for daily transport (i.e. picking up kids or groceries) we found a significant preference for the no-choice above both the ICV and the EV in wave 2. If the respondent lived in a country house, then there was a significant and negative effect for the EV compared to the no-choice alternative in both waves. Overall, there seems to be a tendency for individuals in country houses to have a stronger preference for the no-choice option than other individuals in both waves. For individuals who did not indicate any probable car purchase within the next five years, the effect of purchase price was larger (i.e. more negative) than if a probable purchase was indicated. Furthermore, the data included information about the number of days each individual drove the EV and if they had tried the quick-charge facilities (which were made available to all participants). We tested all these variables but did not find any significant effects. In addition, we tested if the quick-charge dummy had an effect when interacted with public charging possibilities, but did not find any effect.

None of the multi car household parameters for either the EV or the ICV were significant in wave 1, indicating that multi car households do not have different purchase/no purchase preferences compared to one car households. However, the t-test for correlation indicates a significant difference in the preference between the EV and the ICV alternative. In wave 2, there was a slight negative preference towards both the EV and the ICV compared to the no-choice alternative; this suggests that it is easier to choose the no-choice alternative for multi car households. As also found in Jensen et al (2014), the EV alternative was chosen more often by those who are interested in the smallest car classes. Furthermore, the results of this model indicate that individuals interested in the mini car class are less likely to choose the no-choice alternative than others.

3.1 Parameterization of the scale parameter

In the previous model we found that the scale between the before and after datasets was not significant. However, as discussed in the introduction, research shows that preference heterogeneity (mainly random but it can also be systematic heterogeneity) can be confounded with scale heterogeneity. In the interest of exploring this effect and to understand what can cause a change in individual preferences, we also tested whether the effect of scale could be better explained as a function of background characteristics. Thus, for the joint model specification in equation (1 we parameterise the scale difference as follows:

$$\theta_n = \tau + \varphi' x_n, \qquad (2)$$

where x is a vector of explanatory variables. This function is only reasonable if the scale is positive. The results for this model are reported in Table 4. It can be seen that the constant τ measures just about the same effect as in the previous model (Table 3) and that none of the remaining parameters of the scaling coefficient are significant. No improvement was obtained either, as the final log likelihood only passed from -2393 to -2392. In addition to socio-economic characteristics, we also included the number of days the respondent drove the EV, which describes how much experience people got with the EV during the trial period. But, as shown in the results, none of these attributes were significant in explaining difference in scale between the before and after data.

Table 4: Joint model with scale parameterization

	BEFORE					AFTER					
	EV		ICV			EV		ICV			
	Value	Robust t-test	Value	Robust t-test	EV/ ICV	Value	Robust t-test	Value	Robust t-test	EV/ ICV	B/A EV
Linear effects											
Alternative specific constant (α)	5.98	3.86	5.96	2.85		2.11	1.39	8.47	5.25	**	**
Standard deviation for panel effect (σ)	1.54	8.21	3.49	9.12	**	2.12	7.65	3.40	6.63	**	**
Correlation between EV and ICV (ρ)	2.48	7.23				2.82	5.10				
Purchase Price (PP)	-1.67	-5.79	WA			WA		WA			
Fuel costs	-4.60	-3.57	-1.88	-3.77	*	-2.34	-1.37	-1.67	-3.27		
Driving range	1.35	3.62	0.16	1.77	**	3.23	5.78	0.15	1.66	**	**
Carbon dioxide emissions	-0.13	-0.76				-0.22	-1.12				
Battery stations	1.04	3.09				1.31	2.92				
Public charging, slow, shop	0.23	0.89				0.24	0.64				
Public charging, slow, city	-0.11	-0.41				0.74	2.02				*
Public charging, fast, shop	0.52	2.10				0.73	2.09				
Public charging, fast, city	0.51	1.92				0.63	1.60				
Systematic heterogeneity in the alternatives											
Respondent is male	0.22	0.41	0.70	1.14		1.08	1.22	1.03	1.15		
Ref. car class is Mini class	2.84	2.50	1.17	1.10	**	W		W			
Ref. car is Small class	0.05	0.04	-1.36	-1.03	**	1.91	1.57	0.33	0.29	**	
Ref. car is Medium 1 class	0.15	0.14	-0.21	-0.19		-0.23	-0.21	-0.12	-0.10		
Main car is used for commuting	0.86	1.34	0.38	0.48		-1.66	-2.26	-0.66	-1.08	*	**
Main car is used for daily transport	-0.94	-1.00	0.45	0.40	**	-1.64	-2.05	-1.20	-1.68		
Main car is used to pull a trailer	-0.52	-0.87	-0.88	-1.23		W		W			
Ref. purchase is in 1 year	0.24	0.22	0.56	0.52		0.14	0.12	-0.31	-0.30		
Ref. purchase is in 2 years	-0.16	-0.13	0.12	0.10		1.28	1.01	0.51	0.44		
Ref. purchase is in 3 years	1.10	0.73	1.59	1.12		1.14	0.79	0.96	0.79		
Ref. purchase is in 4 years	0.92	0.39	0.84	0.36		0.99	0.68	0.63	0.49		
Ref. purchase is in 5 years or more	0.57	0.32	-0.06	-0.03		0.89	0.55	-1.31	-0.87		
Respondent lives in a city	-0.53	-0.73	-0.21	-0.23		-0.08	-0.07	0.03	0.03		
Type of home is country house	-1.65	-2.12	-1.43	-1.55		-1.84	-1.48	-1.21	-1.19		
Systematic heterogeneity in the attributes											
Battery stations * Multi car HH	-0.38	-0.97				0.57	1.01				
PP * no expected car purchase	-0.46	-2.10	A			-0.63	-2.36	A			
PP * Mini car class	-3.59	-7.03	WA			WA		WA			
PP * Small car class	-1.53	-4.31	WA			WA		WA			
PP * Medium 1 car class	-0.66	-3.27	WA			WA		WA			
PP * ref. purchase is in 1 year	0.54	2.05	WA			WA		WA			
PP * ref. purchase is in 2 years	0.34	1.17	WA			WA		WA			
PP * ref. purchase is in 3 years	0.35	1.08	WA			WA		WA			
PP * ref. purchase is in 4 years	0.57	1.50	WA			WA		WA			
PP * ref. purchase is in 5 years or more	0.68	1.67	1.12	2.24		0.20	0.49	0.99	2.08	*	
Scale parameters											
Constant						0.94	3.07				
Multi car household						-0.11	-0.69				
Respondent is male						0.06	0.41				
Age of respondent is 26-35 years						0.31	0.80				
Age of respondent is 36-45 years						0.30	1.10				
Age of respondent is 46-55 years						0.05	0.20				
Age of respondent is more than 56 years						0.01	0.04				
Ref. car class is Mini class						-0.15	-0.72				
Ref. car is Small class						-0.30	-1.63				
Ref. car is Medium 1 class						-0.09	-0.41				
Quick charge was used in test period						-0.01	-0.07				
Number of days the EV was driven by respondent						0.00	0.29				
Number of obs/individuals	1740/290					1740/290					
Number of parameters = 110											
Log Likelihood = -2392											
Null Log likelihood = -3823											
$\bar{\rho}^2$ = 0.346											

*Significant at 80%, **significant at 95%, T: t-test against 1, A: Alternative specific, W: Wave specific

3.2 ACCOUNTING FOR DIFFERENCES IN PREFERENCES DUE TO KNOWLEDGE OF HAVING BEEN SELECTED

In this section we investigate whether there is a difference in preferences depending on whether individuals knew that they were chosen to participate in the demonstration project. In order to take the different segments into account, we included an interaction effect for each of the attributes in the specification of the utilities for wave 1. Let D_2 be a dummy variable taking the value 1 if the observation belongs to an individual in segment 2 and 0 otherwise. Similarly, let D_3 be a dummy variable taking the value 1 if the observation belongs to an individual in segment 3. The utility specifications for observations in wave 1 are then specified as:

$$\begin{aligned} U^B_{nt,EV} &= \alpha^B_{EV} + \beta'^B_{x,EV} x_{nt,EV} + D_2(\alpha^B_{2,EV} + \beta'^B_{2x,EV} x_{nt,EV}) \\ &\quad + D_3(\alpha^B_{3,EV} + \beta'^B_{3x,EV} x_{nt,EV}) + \beta'^B_{S,EV} S_n + \sigma^B_{EV}\, \zeta_{1n} + \rho^B \zeta_{2n} + \varepsilon^B_{nt,EV} \\ U^B_{nt,ICV} &= \alpha^B_{ICV} + \beta'^B_{x,ICV} x_{nt,ICV} + D_2(\alpha^B_{2,ICV} + \beta'^B_{2x,EV} x_{nt,ICV}) \\ &\quad + D_3(\alpha^B_{3,ICV} + \beta'^B_{3x,EV} x_{nt,ICV}) + \beta'^B_{S,ICV} S_n + \sigma^B_{ICV}\, \zeta_{1n} + \rho^B \zeta_{2n} \\ &\quad + \varepsilon^B_{nt,ICV} \\ U^B_{nt,0} &= \alpha^B_0 + \varepsilon^B_{nt,0} \end{aligned} \tag{3}$$

While the utility specification for observations in wave 2 is like those shown in equation 1. The results from the model estimated in this way are shown in Table .

Table 5: Effect of knowledge of having been selected on individual preferences

	Before					**After**						
	EV		ICV			EV		ICV				
	Value	Robust t-test	Value	Robust t-test	EV/ ICV	Value	Robust t-test	Value	Robust t-test	EV/ ICV	B/A EV	B/A ICV
Linear effects												
Alternative specific constant (α)	5.11	16.34	6.76	18.08	**	1.35	1.26	5.35	3.88	**	**	
Standard deviation for panel effect (σ)	-1.63	-44.28	3.07	44.89	**	1.29	4.24	2.42	3.79	**	**	
Correlation between EV and ICV (ρ)	2.23	29.44				2.05	3.62					
Purchase Price (PP)	-0.97	-18.01	WA			WA		WA				
Fuel costs	-2.12	-7.07	-1.35	-11.34	**	-2.73	-2.08	-1.16	-2.68			
Driving range	0.82	10.58	0.00	0.11	**	2.23	3.90	0.09	1.28	**	**	
Carbon dioxide emissions	-0.20	-2.61	-0.25	-3.81		-0.19	-1.36	A				
Battery stations	0.84	13.23				0.85	2.26					
Public charging, slow, shop	0.06	0.97				0.21	0.86					
Public charging, slow, city	0.10	1.77				0.44	1.69				*	
Public charging, fast, shop	0.37	6.74				0.47	1.99					
Public charging, fast, city	0.35	5.96				0.47	1.74					
Linear effects * Segment 2												
Alternative Specific constant α	-1.26	-2.52	-0.01	-0.01								
Fuel costs	-3.17	-3.25	-0.46	-1.15	**							
Driving range	0.53	1.82	0.05	0.69								
Carbon dioxide emissions	0.17	0.56	-0.29	-1.27	*							
Battery stations	0.52	2.94										
Public charging, slow, shop	0.15	0.69										
Public charging, slow, city	-0.11	-0.55										
Public charging, fast, shop	0.24	1.15										
Public charging, fast, city	0.01	0.04										
Linear effects * Segment 3												
Alternative Specific constant α	-1.02	-1.82	-0.86	-0.93								
Fuel costs	-1.58	-1.41	-0.32	-0.71								
Driving range	0.17	0.52	0.09	1.30								
Carbon dioxide emissions	0.43	1.33	-0.02	-0.08								
Battery stations	-0.15	-0.76										
Public charging, slow, shop	0.21	0.85										
Public charging, slow, city	-0.16	-0.60										
Public charging, fast, shop	0.04	0.18										
Public charging, fast, city	0.12	0.46										
Systematic heterogeneity in the alternatives												
Multi car household	0.19	1.63	-0.07	-0.60	**	-0.09	-0.18	0.00	0.00			
Respondent is male	0.45	4.35	0.55	4.96		0.72	1.68	0.77	1.81	*		
Ref. car class is Mini class	2.17	6.42	-0.05	-0.18	**	0.51	0.38	-0.44	-0.48			
Ref. car is Small class	0.72	2.34	-1.07	-4.02	**	-0.47	-0.37	-0.95	-0.97			
Ref. car is Medium 1 class	0.51	1.67	-0.96	-3.71	**	-2.26	-1.66	-0.88	-0.91		**	
Main car is used for commuting	0.42	3.39	0.41	3.11		-0.31	-0.55	0.20	0.48			
Main car is used for daily transport	-0.22	-1.80	-0.20	-1.53		-1.20	-2.04	-0.94	-2.27		*	*
Main car is used to pull a trailer	-0.33	-3.20	-0.20	-1.76	**	0.14	0.27	0.14	0.26			
Ref. purchase is in 1 year	0.21	0.92	0.16	0.74		1.46	1.36	1.15	1.18			
Ref. purchase is in 2 years	0.07	0.30	0.19	0.83		2.10	1.55	0.74	0.66	*	*	
Ref. purchase is in 3 years	0.49	1.64	0.69	2.44		2.64	1.81	2.07	1.55		*	
Ref. purchase is in 4 years	0.63	1.53	0.49	1.29		1.96	1.24	0.56	0.45	*		
Ref. purchase is in 5 years or more	0.05	0.14	0.22	0.61		1.43	1.09	-0.66	-0.67	*		
Respondent lives in a city	-0.06	-0.42	-0.02	-0.12		-0.61	-0.70	-0.38	-0.36			
Type of home is country house	-0.17	-1.05	-0.53	-3.10	**	-1.33	-2.09	-0.89	-1.50		*	

Table 5 cont.: Effect of knowledge of having been selected on individual preferences

Systematic heterogeneity in the attributes												
Battery stations * Multi car HH	-0.38	-4.72				0.53	1.38				**	
PP * no expected car purchase	0.07	1.25	0.00	0.07		-0.47	-2.28	-0.51	-2.21	*	**	**
PP * Mini car class	-2.76	-17.84	-2.58	-13.89		-2.63	-2.98	-2.28	-2.91			
PP * Small car class	-1.33	-12.72	-1.01	-8.78	**	-0.80	-1.64	-0.85	-1.77			
PP * Medium 1 car class	-0.67	-9.10	-0.41	-5.48	**	-0.13	-0.37	-0.46	-1.54		*	
PP * ref. purchase is in 1 year	-0.05	-0.85	-0.03	-0.43		0.11	0.46	0.01	0.05			
PP * ref. purchase is in 2 years	-0.10	-1.53	-0.09	-1.25		-0.17	-0.53	0.11	0.40			
PP * ref. purchase is in 3 years	-0.13	-1.63	-0.11	-1.32		-0.31	-0.98	-0.18	-0.49			
PP * ref. purchase is in 4 years	-0.16	-1.64	-0.05	-0.46		0.21	0.49	0.58	1.62	*		*
PP * ref. purchase is in 5 years or more	0.00	0.01	0.08	0.71		-0.17	-0.48	0.52	1.72	*		*
scale	1.40	1.17										
Number of obs/individuals	34734/5789					1740/290						
Number of parameters = 157												
Log Likelihood = -27747												
Null Log likelihood = -40071												
$\bar{\rho}^2$ = 0.304												

(*) Significant at 80%, (**) significant at 95%, (T) t-test against 1, (A) Alternative specific, (W) Wave specific

Several attributes become more significant in this case, which is most likely due to the greater number of observations. Specifically, the coefficients for carbon dioxide emissions become significant and with the expected sign in wave 1, but no significant effects were found in wave 2. Furthermore, the coefficients for conventional (slow) charging in city centres becomes significant (at the 90% level) in both waves. However, a significant effect for conventional charging when it was located at shopping centres was still not found.

Since the only difference between segments 2 and 3 is that only the latter answered both survey waves, we would not expect any differences in the interaction effects across segments. Interestingly, however, the parameter for battery stations is positive and significant for segment 2, while it is not significant for segment 3. We controlled whether each interaction parameter was significantly different across the segments, and the parameter for battery stations was the only one. Moreover, there is a tendency for individuals in segments 2 and 3 to be more affected by changes in fuel costs, especially for the EV. Indeed, fuel costs are an important factor for most car users. The results might be affected by their knowledge of having been selected for the demonstration project. Even though it was carefully explained in the survey introduction, that the response to the survey would not affect the chance of being selected and that it was important to give as candid answers as possible, individuals who already knew that their responses were a part of a larger demonstration project, might have taken the survey more seriously and thereby given a more realistic indication of their preferences. Furthermore, in segments 2 and 3 all participants lived in households with a car, and this might mean that they related better to the purchase situation. Even though it was a requirement that there should be at least one car in the household, a few (less than 5%) individuals applied even though they did not live in a household with a car (hence segment 1 includes such individuals). We tested whether there were differences in preferences for no-car owning households and the only significant difference (at the 95% level) was a lower preference for fast charging at shopping centres for individuals in car owning households. Beside these effects, the results did not indicate differences in preferences across the segments.

3.3 The effect of scepticism in the choice of EVs

In this section we analyse the effect of the latent variable, scepticism, in the choice of an EV. A hybrid choice model was used to estimate the effect of scepticism. The specification of the hybrid choice model is the same as reported in Jensen et al. (2013), and is therefore not included herein. The utility specification for the discrete choice component is as reported in the model in Table , but with several parameters restricted across alternatives or waves; the latent variable SC was added as an alternative and wave specific variable in both the utilities for the EV and the ICV.

For the structural equation we tested several observable variables in order to include those who would be relevant either in waves 1 or 2. We found gender, education level, whether the respondent lives in an apartment, whether the respondent lives in a country house, log of respondents income and the number of driving days with the EV during the demonstration project period, to be relevant; however its effects were different before and after getting experience with the EV. The latent variable was linked to these observable variables by a typical structural equation. As reported in Jensen et al. (2014), four indicators were found to be relevant for the latent variable scepticism. These are:

1. New technologies create more problems than they solve
2. When using an EV, I think it would be inconvenient to have to remember to plug it in when the car is parked at home or at other locations
3. I am concerned that EVs are not powerful enough to make a safe takeover
4. If I use an EV instead of a conventional vehicle, I would have to cancel some activities

For statements 2, 3 and 4 we found a significant change both in the mean and in the distribution of the responses on the Likert scale. Statements 2 and 4 focus on the everyday use of EVs. Respondents expressed significantly less scepticism about having to remember to charge the EV after experiencing it, but greater concern about being able to maintain their current mobility. The latter result is most probably due to the relatively short driving distance that current EVs provide compared to conventional cars. In fact, the highest absolute difference in average response between the waves was found for this attitude.

The results of the estimated model are reported in Table 6. Note that on the Likert scale, a higher value indicates a lower indication of agreement. Hence, as all statements used for scepticism were in the direction of being sceptic, a positive value for the variable indicates a less sceptic (or less conservative) individual. The results show that scepticism is only significant for the EV alternative in wave 1. This implies that people indicating a higher level of scepticism have lower preference for EVs before they tried them, but not after. Individuals indicating a higher level of scepticism are not sceptic about ICV, as they know them quite well and this does not change across waves. In wave 2, no significant difference between EV and ICV was found and there seems to be no preference towards choice or no-choice across difference levels of scepticism.

Table 6: Joint hybrid choice model with latent variable for scepticism

	Before					After						
	EV		ICV			EV		ICV			BEF/AF	
	Value	Robust t-test	Value	Robust t-test	EV/ ICV	Value	Robust t-test	Value	Robust t-test	EV/ ICV	EV	IC V
Linear effects												
Alternative specific constant (α)	0.51	0.54	6.30	7.81	**	-1.53	-0.28	11.00	3.24	**		*
Standard deviation for panel effect (σ)	-1.65	-42.50	3.10	44.83	**	1.55	7.74	2.48	7.37	**	**	*
Correlation between EV and ICV (ρ)	2.25	29.24				1.71	4.31				*	
Purchase Price (PP)	-0.97	-19.30	WA			WA		WA				
Fuel costs	-2.20	-7.27	-1.33	-11.20	**	-2.62	-2.04	-1.39	-3.90			
Driving range	0.87	11.61	0.02	1.02	**	2.52	7.16	W		**	**	
Carbon dioxide emissions	-0.23	-6.45	WA			WA		WA				
Battery stations	0.86	13.58				W						
Public charging, slow, shop	0.08	1.50				W						
Public charging, slow, city	0.09	1.68				0.40	2.18				*	
Public charging, fast, shop	0.40	7.66				W						
Public charging, fast, city	0.36	6.62				W						
Linear effects * Segment 2												
Alternative Specific constant α	-0.51	-2.07	0.16	0.70	**							
Fuel costs	-1.98	-2.83	-0.64	-2.28	*							
Battery stations	0.22	1.61										
Systematic heterogeneity in the alternatives												
LV Scepticism	1.08	4.86	0.11	0.63	**	0.72	0.56	-0.84	-0.97			
Multi car household	0.18	1.53	-0.12	-0.97	**	-0.26	-0.51	-0.24	-0.5			
Respondent is male	0.43	4.47	WA			WA		WA				
Ref. car class is Mini class	2.19	7.75	0.12	0.48	**	0.91	1.23	-0.15	-0.23	**	*	
Ref. car is Small class	0.89	2.99	-1.11	-4.28	**	-0.19	-0.2	-1.4	-1.68	**		
Ref. car is Medium 1 class	0.62	2.15	-1.04	-4.20	**	-1.34	-1.53	-1.02	-1.24		**	
Main car is used for commuting	0.40	3.09	A			-0.46	-1.06	A			*	*
Main car is used for daily transport	-0.16	-1.29	A			-0.49	-1.03	A				
Main car is used to pull a trailer	-0.35	-3.46	-0.18	-1.65	**	-0.19	-0.43	A				
Ref. purchase is in 1 year	0.16	0.84	A			1.05	1.7	0.91	1.77		*	*
Ref. purchase is in 2 years	0.13	0.59	A			0.87	1.35	0.50	1.03			
Ref. purchase is in 3 years	0.70	2.73	A			0.85	1.23	0.67	0.96			
Ref. purchase is in 4 years	0.55	1.58	A			1.51	1.63	1.5	1.79			
Ref. purchase is in 5 years or more	0.14	0.44	A			0.415	0.49	0.222	0.26			
Respondent lives in a city	-0.03	-0.21	WA			WA		WA				
Type of home is country house	-0.14	-0.91	-0.58	-3.47	**	-0.84	-2.01	W			*	
Systematic heterogeneity in the attributes												
Battery stations * Multi car HH	-0.39	-4.85				0.62	2.44				**	
PP * no expected car purchase	0.05	0.91	A			-0.36	-1.46	-0.42	-1.55		*	*
PP * Mini car class	-2.72	-22.2	WA			WA		WA				
PP * Small car class	-1.38	-13.1	-1.00	-8.73	**	-0.94	-2.42	A				
PP * Medium 1 car class	-0.71	-9.76	-0.4	-5.48	**	-0.34	-1.51	A			*	
PP * ref. purchase is in 1 year	-0.03	-0.65	WA			WA		WA				
PP * ref. purchase is in 2 years	-0.11	-1.96	WA			WA		WA				
PP * ref. purchase is in 3 years	-0.16	-2.38	WA			WA		WA				
PP * ref. purchase is in 4 years	-0.09	-1.03	WA			WA		WA				
PP * ref. purchase is in 5 years or more	-0.00	-0.01	WA			WA		WA				

Table 6 cont.: Joint hybrid choice model with latent variable for scepticism

	Before					After						
											BEF/AF	
	Value	Robust t-test				Value	Robust t-test					
Latent Variable Structural Model												
Intersect (κ)	3.96	82.07				3.57	10.27					
Std. deviation for error term (σ_ω)	-1.01	-20.00				-1.20	-4.79					
Respondent is male	0.06	3.09				0.07	1.08					
Respondent has a high education level	0.04	0.35				0.50	1.96				*	
Respondent lives in an apartment	0.04	1.20				-0.74	-2.59				**	
Respondent lives in a country house	-0.03	-1.31				-0.16	-1.60					
Log of respondents income	0.03	3.27				0.04	0.81					
Number of driving days with EV						0.004	2.78					
Latent Variable Measurement Equation												
Std. dev. for indicator 1 (σ_1)	-0.21	-14.50				-0.21	-4.34					
Intercept for indicator 2 (γ_2)	-3.78	-6.55				-7.13	-1.94					
Linear effect of indicator 2 (α_2)	1.84	13.26				2.70	2.95					
Std. dev. for indicator 2 (σ_2)	-0.09	-4.43				-0.08	-0.71					
Intercept for indicator 3 (γ_3)	-1.86	-6.47				-2.13	-1.27					
Linear effect of indicator 3 (α_3)	1.37	19.94				1.58	3.80					
Std. dev. for indicator 3 (σ_3)	-0.12	-7.33				-0.03	-0.38					
Intercept for indicator 4 (γ_4)	-2.67	-5.34				-2.40	-1.27					
Linear effect of indicator 4 (α_4)	1.58	13.09				1.13	2.38					
Std. dev. for indicator 4 (σ_4)	0.06	4.42				0.16	3.58				**	
Scale	1.30	1.98										
Number of obs/individuals	34734/5789			1740/290								

Number of parameters = 130
Log Likelihood (choice model) = -27803
Null Log likelihood (choice model) = -40071
$\bar{\rho}^2$ = 0.303

(*) Significant at 80%, (**) significant at 95%, (T) t-test against 1, (A) Alternative specific, (W) Wave specific

3.4 COMPARISON BETWEEN ORTHOGONAL AND EFFICIENT DESIGN

The model presented in Jensen *et al.* (2013) was estimated on data from the pilot, where an orthogonal design was used to build the SP experiment. To compare data from the two surveys, we estimated a similar model on data from the final survey. As not all attributes and background information are the same, it was not possible to estimate exactly the same models, but for those variables available in both datasets, the same specification was used. Looking directly at the parameters in each model, their values seem different, but when calculating the willingness to pay, similar effects are obtained for most variables. In particular, all parameters related to fuel costs and driving range are very similar for the EV alternative, but somewhat different for the ICV alternative. This might be due to the lower significance of the estimated parameters (and hence a larger confidence interval), but it could also be due to the presence of the no-choice alternative in the final survey. However, we lack knowledge as for the reasons why this should affect the ICV alternative more than the EV alternative.

The final survey also contains fewer observations. The effect of carbon dioxide emissions is quite different, and the estimated parameter in the final survey has lower significance. In general, willingness to pay is lower in the final survey than in the pilot for almost all effects. The effect of environmental concern is positive and stable between waves in both models. We found contradictory results for the purchase price only in the case of individuals who did not indicate any expected car purchase. However, the questions leading to the reference purchase are quite different in the two applications. In the pilot, a recent car purchase (within the last five years) was first asked for. If no such purchase had taken place, a future car purchase was instead asked for. In the final survey, only a future car purchase was asked for.

Table 7: Joint Hybrid Choice model with latent variable for environmental concern

	PILOT SURVEY					**FINAL SURVEY**				
	Before		After			Before		After		
	Value	Robust t-test	Value	Robust t-test	B/A	Value	Robust t-test	Value	Robust t-test	B/A
Linear effects										
Alternative specific constant (α)	-0.32	-0.47	-2.7	-3.4	**	2.19	0.8	-2.03	-0.71	**
Standard deviation for panel effect (σ)	1.13	8.25	-1.46	-8.83	**	1.63	8.36	2.2	7.02	*
Purchase Price (PP)	-0.59	-7.24	W			-1.3	-8.36	W		
Fuel costs (EV)	-2.42	-4.73	W			-5.31	-3.84	W		
Fuel costs (ICV)	-0.95	-3.12	-1.69	-4.66	*	-1.97	-3.56	-1.14	-1.6	
Driving range (EV)	0.776	4.28	1.62	6.61	**	1.49	3.58	3.56	5.81	**
Driving range (ICV)	0.045	2.07	W			0.17	1.72	W		
Carbon dioxide emissions	-0.55	-5.06	W			-0.191	-1.29	W		
Top speed (0-120km/h)	2.81	2.24	5.24	3.9	*					
Top speed (120-160km/h)	1.17	3.59	0.056	0.15	**					
Top speed (over 160km/h)	0.065	0.37	W							
Battery stations	2.72	6.09	W			1.63	4.78	W		
Battery life	0.345	4.26	0.537	4.93	*					
Charging option at work	0.251	2.67	W							
Public charging, city and Train stations	0.553	4.77	0.335	2.49	*					
Public charging, city	0.459	4.87	W							
Public charging, Train stations	0.332	3.51	W							
Public charging, slow, shop						0.22	0.91	W		
Public charging, slow, city						-0.154	-0.55	0.573	1.81	**
Public charging, fast, shop						0.556	2.31	W		
Public charging, fast, city						0.462	1.81	W		
Systematic heterogeneity in the attributes										
PP * no expected car purchase	0.542	3.21	W			-0.564	-1.58	W		
PP * ref car is a used car	-0.4	-3.63	W							
PP * Mini car class	-1.81	-3.19	-3.16	-3.39	*	-3.21	-5.02	-4.11	-5.06	
PP * Small car class	-1.02	-4.86	W			-1.28	-3.73	W		
PP * Medium 1 car class	-0.5	-4.03	W			-0.69	-3.08	W		
Driving range * multi car household	-0.22	-0.96	-0.6	-2.55	**	-0.0319	-0.28	0.0916	0.76	**
Battery stations * Multi car household	-1.81	-2.64	0.051	0.07	**	-1.12	-2.66	0.5	1	**
Charging at work * >km workdistance	0.397	2.89	W							
Systematic heterogeneity in the EV alternative										
Ref. car class is Mini class	1.42	4.87	W			1.55	3.31	W		
Ref. car is Small class	0.86	3.51	W			1.5	3.57	W		
Ref. car is Medium 1 class	0.477	2.02	-0.01	-0.02	*	0.582	1.43	-0.313	-0.62	*
Multi car household	0.896	2.35	W			0.755	0.8	W		
Ref. Car is a used car (0-5 years old)	0.47	2.57	W							
Ref. Car is a used car (5-10 years old)	0.991	4.73	W							
Respondent is male	-0.48	-3.15	W			-0.454	-2.06	W		
Latent variable environmental attitude	1.86	5.12	W			1.37	1.67	W		
scale	0.908	0.99^{T}				0.863	1.09^{T}			

Table 7 (Cont.): Joint Hybrid Choice model with latent variable for environmental concern

	PILOT SURVEY					FINAL SURVEY				
	Before		After			Before		After		
	Value	Robust t-test	Value	Robust t-test	B/A	Value	Robust t-test	Value	Robust t-test	B/A
Structural model										
Intersect (κ)	1.32	10.35	1.41	11.01	**	2.97	33.54	3.03	33.17	*
Std. deviation for error term (σ_ω)	-1.38	-15.3	-1.22	-14.8	*	-1.22	-5.61	-1.4	-5.75	*
Age of respondent is 26-35 years	0.152	1.37	W			-0.0962	-1.1	W		
Age of respondent is 36-45 years	0.19	1.7	W			-0.168	-2.01	W		
Age of respondent is 46-55 years	0.17	1.57	W			-0.222	-2.55	W		
Age of respondent is 56-65 years	0.259	2.21	W			-0.139	-1.6	W		
Age of respondent is over 65 years	0.288	2.18	W			0.143	0.84	W		
Car purchase is Mini class	-0.14	-2.45	W			0.033	0.86	W		
Number of cars in household	0.133	4.1	W			0.0573	1.9	W		
Measurement equation										
Std. dev. for indicator 1 (σ_1)	-0.56	-20.2	W			-0.142	-4.3	W		
Intercept for indicator 2 (γ_2)	0.77	3.43	W			-1.89	-1.74	W		
Linear effect of indicator 2 (α_2)	1.17	9.42	W			1.53	4.14	W		
Std. dev. for indicator 2 (σ_2)	0.095	4.21	W			-0.278	-6.52	W		
Intercept for indicator 3 (γ_3)	-0.97	-3.49	W			-4.79	-2.83	W		
Linear effect of indicator 3 (α_3)	1.53	9.19	W			2.48	4.27	W		
Std. dev. for indicator 3 (σ_3)	-0.23	-5.98	W			-0.243	-3.82	W		
Intercept for indicator 4 (γ_4)	-0.97	-3.78	-1.49	-4.8	*	-2.73	-2.37	W		
Linear effect of indicator 4 (α_4)	1.46	9.33	1.79	9.63	*	1.57	3.99	W		
Std. dev. for indicator 4 (σ_4)	-0.52	-8.92	-0.28	-5.17	**	-0.379	-6.81	-0.233	-3.61	*
Intercept for indicator 5 (γ5)	-0.8	-4.04	W							
Linear effect of indicator 5 (α5)	1.44	12.05	W							
Std. dev. for indicator 5 (σ5)	-0.37	-11.2	W							
Intercept for indicator 6 (γ6)	0.096	0.43	W							
Linear effect of indicator 6 (α6)	1.34	10.18	W							
Std. dev. for indicator 6 (σ6)	-0.18	-6.83	W							
Intercept for indicator 7 (γ7)	-0.61	-2.67	W							
Linear effect of indicator 7 (α7)	1.45	10.44	W							
Std. dev. for indicator 7 (σ7)	-0.22	-6.54	W							
Number of individuals	369		369			290		290		
Number of observations	2952		2952			1740		1740		
Number of parameters	79					57				
Log Likelihood (choice model)[1]	-3124					-1129				
Log Likelihood NULL (choice model)	-4092					-1848				
$\bar{\rho}^2$	0.223					0.364				

(*) Significant at 80%, (**) significant at 95%, (T) t-test against 1, (A) Alternative specific, (W) Wave specific

[1] The large differences between the log likelihood between the models are due to differences in the estimation method. In the model for the pilot data, each indicator for the individuals was repeated as many times as the individual had SP tasks. Although this problem in the estimation was solved later, we kept the first model for comparison with the model presented in the paper.

4 CONCLUSIONS

In this paper we explored different sources of variation in preferences for electric vehicles (EV), and in particular sources of variation in preferences before and after individuals have tried an EV in real life. The data available provided experimental choices between an EV, a conventional vehicle and a no-choice alternative, from individuals before and after they had an EV available for a period of three months. Furthermore, the data provides responses to attitudinal statements regarding scepticism and environmental concern. Beside the effect of EV experience, we investigated the effect of prior knowledge of having been selected for an EV demonstration project, the effect of scale between datasets and the effect of scepticism. Firstly, we found that the results obtained with the final survey (collected with an efficient design) confirmed almost all the results found with the big pilot (collected with the orthogonal design). While we did not expect results should change, it was reassuring to find that results were confirmed in both surveys. We found that with more experience, preferences changed only for the EV alternative. In particular, before the individuals obtained experience with an EV, only preferences for quick charging solutions were significantly different from zero, while experienced individuals also found conventional charging useful when located in city centres. In general we did not find large differences between those who knew they were selected to participate in the EV demonstration project. We found, however, that those who knew that they were selected indicated stronger preferences for fuel costs and the number of battery stations. Respondents who know that they have been selected to participate might be more dedicated when answering the survey and hence these effects appear stronger. In general, we did not find any scale differences between the before and the after data, not on average nor as a function of socio-economic characteristics or length of using the EV in real life. Finally, we found that individuals who are more sceptic (conservative) indicated lower preferences for the EV before the experience, whereas this effect was not significant after the experience.

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PREDICTING THE POTENTIAL MARKET FOR ELECTRIC VEHICLES

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ABSTRACT

Forecasting the potential demand for electric vehicles is a challenging task. As most studies for new technologies rely on stated preference (SP) data, market share predictions will reflect shares in the SP data and not real markets. Moreover, typical disaggregate demand models are suitable to forecast demand in relatively stable markets, but show limitations in the case of innovations. When predicting the market for new products it is crucial to account for the role played by innovation and how it penetrates the new market over time through a diffusion process. Unfortunately, typical diffusion models in marketing research use fairly simple demand models. In this paper we discuss the problem of predicting market shares for new products and suggest a method that combines a choice model with a diffusion model to taking into account that new products often need time to obtain a significant market share. Results show that typical discrete choice models forecast a demand either too restrictive in the long period or too optimistic in the short period. Accounting for the diffusion effect, instead allows predicting the slow penetration of the initial years and a greater market share as the market becomes more mature correctly.

1 INTRODUCTION

Electric vehicles (EVs) have faced extreme difficulties in developing into a mass marketed product. With recent introductions of new models from several producers, the need for reliable predictions of future demand is greater than ever. Discrete choice modelling is a popular tool for predicting car demand. A well-known problem related to the prediction of EV demand, is that most discrete choice models for new technologies rely on hypothetical stated preference (SP) data. When these models are used for prediction, alternative-specific constants (ASCs) and eventually scale, need to be adjusted to reflect that unobserved factors may vary between the hypothetical setting and the real market (Train 2009).

Consequently, many studies on demand for EVs using SP data only present model estimations and/or trade-offs between coefficients but do not provide forecasts, (Beggs et al. 1981; Ramjerdi & Rand 2000; Potoglou & Kanaroglou 2007; Hidrue et al. 2011; Ito et al. 2013). A few studies (Adler et al. 2003; Knockaert 2005) present models estimated on SP data which are intended for larger simulations systems, but do not report how these models would be integrated. Aware of the limitations of SP data, most studies use the estimated coefficients to compare EV market shares in different scenarios (Calfee 1985; Bunch et al. 1993; Ewing & Sarigöllü 2000; Dagsvik et al. 2002; Mabit & Fosgerau 2011; Glerum et al. forthcoming), but do not claim that they are actual forecasts. Brownstone et al. (2000) used joint RP/SP models. They found that the joint RP/SP estimation gave a much lower EV market share (18% instead of 42%) than when using only SP data. Batley et al. (2004) used SP data collected in the UK and re-calibrated the Alternative Specific Constants (ASCs) using the USA market shares found by Brownstone et al. (2000). Using results from other countries to re-estimate the ASCs might be an appropriate solution in the absence of better information, but results are sensitive to the reference market shares used to re-calibrate the ASC, so care must be taken on the type of market considered as reference and the characteristics of that market.

Jensen et al. (2013) show that in research on alternative-fuel vehicles where respondents have none, or very little experience with the products presented, the direct experience with the new product changes individual preferences for specific EV characteristics. Their study suggests that individuals' preferences change as people acquire more knowledge about the product. Thus, this effect needs to be considered when forecasting the potential demand for EVs.

Typical disaggregate demand models (as used in all papers above) are suitable to forecast the demand for relatively stable markets, but show limitations in the case of innovation. Glerum et al. (forthcoming) tried to explicitly account for the lack of EV market shares, however they do not deal with the evolution of demand over time. There is an important literature on dynamic vehicle holding models (where the holding in one time period depends on the past or future time periods) and vehicle transaction models, but this mainly refers to conventional cars and does not explicitly consider the effect of innovation. Innovations often diffuse slowly and need time to obtain a significant market share, but this process cannot be properly reproduced with typical demand models. The diffusion process has been defined as the process by which an innovation is communicated through certain channels over time among members of a social system (Rogers 2010). The behavioural assumption in these models is that an innovation is first adopted by a segment called *innovators*, who are willing to adopt a product despite, perhaps, a high price or low reliability, whereas adoption by another segment, the *imitators*, depends on the number of adoptions that have already occurred.

Marketing studies include many examples that investigate diffusion processes. The main limitation of these studies is that they mainly look at the diffusion process of a single product and when they account for substitution among products, they typically use very simple demand models. The most popular diffusion model today is the one of Bass (1969), which did not account for the influence of competitive products. To account for this effect, some authors (i.e. Weerahandi & Dalal 1992; Jun & Kim 2011) have combined a

Bass diffusion model with a logit model to simultaneously capture the diffusion process and the replacement process in a multi-product framework. However, most studies use aggregate demand models based on market share time series data to estimate the joint diffusion/substitution model. Weerahandi and Dalal (1992) used a disaggregate demand model, but only included two disaggregate variables.

We envisage that the diffusion effect can be one of the reasons behind the delay of the EV market penetration. Hence, the effect of the diffusion needs to be considered when predicting market shares. At the same time, the characteristics of EVs and their recharging options play a crucial role in explaining demand for EVs, but current diffusion models are not able to represent the substitution effect among car types adequately. The objective of this paper is to discuss the prediction of EV market shares, and to suggest a method that combines a diffusion model, as typically estimated in the marketing literature, with advanced discrete choice models, without losing the advantage of an appropriate specification estimated at disaggregate level, as typically done in the transport literature.

The rest of the paper is organized as follows. In section 2 we discuss the problem of predicting market shares. We first describe the method using discrete choice models and then the diffusion model. In Section 3 we discuss the problem of forecasting the market share for EVs and present a method to combine the diffusion models with advanced discrete choice models. In section 4 we describe an example of application of the methodology described in section 3, and the data we used for this. Section 5 presents the results and discusses our most interesting findings. In section 6 we summarize and conclude.

2 PREDICTING DEMAND FOR NEW PRODUCTS

2.1 PREDICTING WITH DISAGGREGATE CHOICE MODELS

Demand models are estimated mainly to forecast demand. They are estimated for a specific context and then, assuming that the demand curve is stable (i.e. the coefficients do not vary), they are used to forecast the demand in future years. Demand models are typically estimated at the disaggregate level, while forecasts usually represent the behaviour of an entire population (or market segment). At the same time, disaggregate models are often estimated using a sample of observations from the population. Then, given a disaggregate model estimated on a sample, to use this model in forecasting we usually require: (1) to aggregate the model to the population segment of interest; (2) to change the value of the attributes according to the policy scenarios and to represent the variation in the decision makers characteristics, and (3) to adjust the segments dimension to reflect changes over time in the number of decision makers in the population.

Different methods can be used to aggregate models estimated at the disaggregate level (see Ortúzar and Willumsen 2011, pages 338-341; Train 2009, pages 29-32; Ben-Akiva and Lerman 1985, pages 131-148). The easiest way is to use average values and if the model was linear this would be correct. But as the models are non-linear, aggregation based on a representative consumer is biased. Therefore aggregate values for the market shares are most often obtained with *sample enumeration*. Purposely designed synthetic samples can also be used in an enumeration approach (Gunn et al. 1982). With this method, a random sample of the population is used as representative of the entire population. If the sample is non-random, the population is classified into groups, and the estimated market share is calculated as a weighed sum of the within-class forecasts.

Consider for simplicity a logit model estimated on a sample, assumed to be representative of the population: $\hat{\beta}$ is a vector of estimated coefficients, x_{ni} a vector of attributes, λ the unknown scale of the model in the estimation context (usually set equal to one and not estimated), $A\hat{S}C$ a full set of estimated alternative specific constants ensuring that the model reproduces the observed market shares in the sample and N the reference population in the estimation year. Then the aggregate market share of alternative i is given by:

$$MS_i = \frac{1}{N}\sum_{n=1}^{N} P_i = \frac{1}{N}\sum_{n=1}^{N} \frac{\exp\left(\lambda\left(A\hat{S}C_i + \hat{\beta}' \cdot x_{ni}\right)\right)}{\sum_j \exp\left(\lambda\left(A\hat{S}C_j + \hat{\beta}' \cdot x_{nj}\right)\right)} \tag{1}$$

The model can then be used to forecast demand based on assumptions about the values of the variables that enter the model in this scenario. Often it is necessary to adjust the constants and the scale to reflect the fact that the unobserved factors are different between the estimation and prediction contexts. This is the typical problem of model transferability (Ortúzar and Willumsen 2011, pages 341-345). It is also the typical problem encountered when models are estimated using SP data. The problem can be easily solved if aggregate real market shares are available for the new context. If the scale also needs calibration, market shares for two points in time are necessary.

Once a model is available (correctly adjusted to reproduce the baseline market shares), an iterative method can be used to adjust the constants. This consists in comparing the estimated and actual shares until they are sufficiently close to each other:

$$A\hat{S}C_j^{t=1} = A\hat{S}C_j^{t=0} + \ln\left(MS_j/\widehat{MS}_j^{\,t=0}\right) \tag{2}$$

This simple method allows for adjusting the ASC only. To adjust both for ASC and scale we would need to update the vector of attributes (x_{nj}^t) at the future time t and re-estimate the model using the following utility:

$$U_{nj}^t = ASC_j^t + \lambda^t\left(\widehat{\beta'} \cdot x_{nj}^t\right) + \varepsilon_{nj}^t, \tag{3}$$

where β are assumed to be fixed over time and equal to the coefficients estimated in the base year, while the coefficients $\left(ASC_j^t, \lambda^t\right)$ are estimated in the new situation.

Most often SP data is used to study products not currently available, for which there is not yet a real market share available. This represents one of the major problems when dealing with prediction of the EV market. If the coefficients are estimated using RP and SP data jointly (as in Brownstone et al., 2000), then the scale of the model is correct because it is set to the RP data, while the constants can be adjusted according to the RP situation. If the coefficients are estimated using only SP data, there is no clear solution (Cherchi & Ortúzar 2006). Glerum et al. (forthcoming) make some corrections of their SP model in order to reflect the real market situation. Since part of their sample only had the choice between a conventional Renault and an electric Renault, they impute an extra alternative that represents other gasoline cars on the market and correct the alternative specific constants so that the ratio between Renault and the competitors are preserved. However, for the EV alternative, they assume that the response rates to the SP questionnaire would represent the state of the market if electric vehicles were released at the time of the study. They found a market share for EV of 27%, which must be considered quite high for the initial years.

2.2 DIFFUSION MODELS

Diffusion models are built based on the behavioural theory that an innovative product is usually adopted first by a few people ("innovators"), who in turn, influence others ("imitators") to adopt the product. The popular diffusion model following Bass (1969), states that the number of new adopters a_t during period t is defined as:

$$a_t = \left(p + q\frac{Y_{t-1}}{M_t}\right)(M_t - Y_{t-1}), \tag{4}$$

where Y_{t-1} is the cumulative number of adoptions that occurred before period t, M_t is the number of potential adopters, p is the coefficient of innovation, capturing intrinsic tendency to adopt as well as the effect of time invariant external influences) and q is the coefficient of imitation, capturing the fact that the adoption probability of customers increases with the proportion of eventual adopters who have already adopted.

The Bass model is a good starting point for forecasting the long-term penetration pattern of new technologies and products under two types of conditions (Lilien et al. 2000): (1) a product has recently been introduced and the penetration has been observed for a few time periods, or (2) the product has not yet been introduced, but it is similar in some way to existing products or technologies where the diffusion history is known. These conditions are required in order to estimate the unknown coefficients in the Bass model. According to (Lilien et al. 2000), data must be available for at least four periods to allow estimation of p and q. If no such data is available, parameters estimated for historical innovations that are similar to the innovation being studied are often used instead. To make use of equation (4) revealed preference data describing whether the customers adopted the product or not are needed.

Several approaches have been suggested to extend the basic diffusion model to account for the inter-relationship among various products, i.e. the substitution dynamic effects among products. In particular, Jun and Park (1999) present one of the first attempts to incorporate diffusion and substitution effects (i.e. a discrete choice model) into an integrated model. More specifically, they include the diffusion effect (though different from the Bass specification) directly into the utility of subscribing for the durable technology i (i.e. of generation i) at the time period t:

$$V_t^i = q^i(t - \tau^i + 1) + \beta'^i \cdot x_t^i, \tag{5}$$

where x_t^i is a vector of attribute values for generation i at time period t , β^i is a vector of corresponding coefficients, q^i is the time dependent diffusion effect related to each product generation and τ^i is the year when a product of generation i was introduced to the market. They argue that the time variables may capture most of the effects of the unavailable attributes (or exogenous variables). Note that they do not include ASCs in the specification which they do not comment on further. This is interesting because, although they do not mention it, in one application of their model, they estimated diffusion terms specific for each generation, which to some extent captures the same effect as the ASCs in the typical discrete choice models.

Assuming an identically and independently distributed (iid) Extreme Value type 1 (EV1) error term for first time buyers at time t, they computed the probability ($P_t^{0,k}$) to purchase or not and which generation k to purchase; in case of consumers already using i-th generation products at time t they computed the probability ($P_t^{i,k}$) to upgrade or not and which generation k to choose:

$$P_t^{0,k} = \frac{\exp(V_t^{0,k})}{\exp(c) + \sum_j \exp(V_t^{0,j})}; \quad P_t^{i,k} = \frac{\exp(V_t^{i,k})}{\sum_j \exp(V_t^{i,j})}; \quad \forall j, k > i, \tag{6}$$

where c is a constant, included in the utility of the non-purchase alternative, assumed to be constant in the diffusion period.

If the number of products in use for each time period is available and hence data is available for both new purchases and upgraders from one category to subsequent categories, then the net sales model is the sum of the first buyer plus the new up-graders minus the current adopters of generation k who change to another generation j:

$$S_t^k = (M_t - Y_{t-1}) \cdot P_t^{0,k} + \sum_{i=1}^{k-1} Y_{t-1}^i P_t^{i,k} - Y_{t-1}^k \sum_{j=k+1}^{n_t} P_t^{k,j} , \qquad k = i+1, i+2, \dots, n_t \tag{7}$$

where M_t is the potential market share at time t, Y_{t-1} the total number of product in use[1] at time t-1, Y_{t-1}^i the number of adopters using products of the i-th generation at time t-1, and n_t is the number of generations available at time t.

If the data does not allow distinguishing between replacement and first purchase demand (i.e. total sales in each time period), they use the same method for both first time buyers and replacements. A purchase is then counted in the market potential as many times as he or she upgrades to the new generation or makes a first purchase. The number of sales in each period would be:

$$S_t^k = (M_t - Y_{t-1}) \cdot P_t^k = (M_t - Y_{t-1}) \cdot \frac{\exp(V_t^k)}{\exp(c) + \sum_j \exp(V_t^j)} \tag{8}$$

and the total number of sales every year would be:

$$Y_t = Y_{t-1} + \sum_{k=1}^{n_t} S_t^k \tag{9}$$

Although the model is fairly general, for estimation purposes they make the assumption that the potential market share at each time period t is equal to the potential market share of each generation k (i.e. $M_t = M_k$) and it is not affected by the marketing variables, but remains constant. In their most advanced application the utility (eq. 7) depends only on one attribute (the price), but its coefficient is different for the various generations of the product, the final model includes a total of nine coefficients estimated simultaneously (four price coefficients, four market share values and the constant c).

Further developments of the joint diffusion/substitution model have mainly worked in the direction of accounting for the different substitution effects that can take place over time (such as the possibility that new adopters can switch back to the old product or postpone the choice decision skipping previous generations and directly adopting a newer generation, (e.g. Jun & Kim 2011; Jiang & Jain 2012), but the substitution models are always used with basic structures. As opposed to Jun and Park (1999), most of them model the Bass formulation explicitly (as in eq. 4).

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[1] This accounts implicitly for the replacement by newer generations; as such, it can decrease while cumulative sales do not decrease. Therefore, it is different from the cumulative sales.

In these more advanced diffusion/substitution models all coefficients are estimated simultaneously. This is complicated and requires substantial data on the real market shares. This is (at least so far) not available for the EV market. On the other hand the substitution models used in the diffusion literature are very simple; they include few attributes to define the product (usually only the cost) and they are specified at the aggregate level. Since EVs are still under development, almost all of their characteristics are likely to change significantly in the future. As such, it is crucial to use a substitution model that captures properly the effect of these characteristics on the EV demand.

3 COMBINING DISAGGREGATE MODELS AND DIFFUSION MODELS

As mentioned before, transport research uses fairly sophisticated disaggregated substitution models, but diffusion is not accounted for. Instead, in marketing diffusion is accounted for in a highly sophisticated way but the substitution models are fairly simple. The idea behind the method we propose consists of replacing the probabilities in Eq. 7 with the models estimated at a disaggregate level, assuming that the trade-offs are stable over time, and re-estimating only the scale and ASC to adjust to the observed market shares. Hence, following Jun and Park's work (though the method can be applied to any type of diffusion model), the probability of choosing category k can be written as:

$$P(0,k) = \frac{\exp(\lambda\ (ASC_t^k + q^k(t-\tau^k+1) + \hat{\beta}' \cdot x_t^k))}{\exp(ASC_{nobuy}) + \sum_j \exp(\lambda\ (ASC_t^j + q^j(t-\tau^k+1) + \hat{\beta}' \cdot x_t^j))},$$
$$P(i,k) = \frac{\exp(\lambda\ (ASC_t^k + q^k(t-\tau^k+1) + \hat{\beta}' \cdot x_t^k))}{\sum_j \exp(\lambda\ (ASC_t^j + q^j(t-\tau^j+1) + \hat{\beta}' \cdot x_t^j))} \qquad (10)$$

where $\hat{\beta}$ is a vector of estimated coefficients from the disaggregate model. The remaining coefficients, in particular ASC and scale, will be estimated in the joint diffusion/substitution model. The model structure can be any discrete choice model less restrictive than the simple multinomial logit (MNL) model. For example, Brownstone (2000) and Hensher and Greene (2001) applied mixed logit models to study vehicle type choice.

Then, when estimating the demand in equation (7) or (8), instead of estimating the $\beta's$, as in Jun and Park (1999), we need to estimate the scale (λ) and ASCs together with the diffusion, while the $\beta's$ are those estimated from a disaggregate model.

The demand model in equation (10) can be extended to account for different types of substitution as in the more advanced diffusion models briefly discussed in section 2.2. However, if a suitable disaggregate model is available, the procedure can be applied without further assumptions. Therefore, the application of the joint diffusion/discrete choice model to predict EV demand is mainly limited by the lack of sufficient data with enough detail (as all transactions are needed) and with enough variability to allow estimation of the coefficients of the diffusion model. It is also important to mention that choice of an EV is part of the car transaction problem and, as such, is very complicated. However, we can assume that individuals choose first whether to buy a car and then whether to adopt and hence, eventually, choose an EV. In this paper we focus on the second part, while the first can be modelled as described, for example, by de Jong (1996) or Goldberg (1998).

4 DATA AND MODELS USED TO PREDICT EV MARKET SHARES

In this section we show how the model in equation (10) can be applied to the specific case of predicting the market penetration of EVs. The practical application of the model is of course limited by the data available and the model structures estimated with the available data. The section also reports a description of the data, the disaggregate model available and the scenarios set up to make the forecast.

4.1 EMPIRICAL MODEL DEVELOPMENT

Following the specification from Jun and Park (1999), we defined the utility of choosing an EV and a conventional internal combustion engine car (ICVs) as:

$$\begin{aligned} V_t^{EV} &= ASC^{EV} + q^{EV}(t - \tau^{EV} + 1) + \hat{\beta}'^{EV} \cdot x_t^{EV} \\ V_t^{ICV} &= ASC^{ICV} + \hat{\beta}'^{ICV} \cdot x_t^{ICV} \end{aligned} \tag{11}$$

where q^{EV} is the parameter catching the effect of diffusion, τ^{EV} is the time when the EV alternative was introduced on the market, $\hat{\beta}^{EV}$ and $\hat{\beta}^{ICV}$ are the coefficients for x_t^{EV} and x_t^{ICV} which are characteristics of the EV and the ICV alternatives, ASC are the alternative specific constants (at least one needs to be normalised). The diffusion effect is only included in the utility for the EV alternative, as we assume that the ICV alternative has been fully adopted by the population. Due to the available data, we do not include a no-choice alternative as in Jun and Park (1999).

Let M_{EV} be the market potential of the EV alternative and Y_{t-1}^{EV} be the cumulative number of EV sales before time period t. The number of EV sales in period t is then calculated as:

$$S_t^{EV} = (M^{EV} - Y_{t-1}^{EV}) \cdot \Pr(EV_t), \tag{12}$$

Or more specifically:

$$S_t^{EV} = (M^{EV} - Y_{t-1}^{EV}) \cdot \frac{\exp(ASC^{EV} + q^{EV} \cdot (t - \tau^{EV} + 1) + \lambda \cdot \hat{\beta}'^{EV} \cdot x_t^{EV})}{\exp(ASC^{ICV} + \lambda \cdot \hat{\beta}'^{ICV} \cdot x_t^{ICV}) + \exp(ASC^{EV} + q^{EV} \cdot (t - \tau^{EV} + 1) + \lambda \cdot \hat{\beta}'^{EV} \cdot x_t^{EV})} \tag{13}$$

where $\hat{\beta}^{EV}$ and $\hat{\beta}^{ICV}$ are estimated in the disaggregate model using SP data (as described in the section below) and get fixed in the diffusion process. q_{EV}, λ and the ASCs will be estimated as part of the diffusion process. Note that since ASC and q^{EV} are estimated, the scale can be applied only to the coefficients estimated in the disaggregate choice model which are kept fixed.

4.2 DISAGGREGATE DEMAND MODEL FOR SUBSTITUTION

To model the future demand of EV, we use a discrete choice model estimated on stated choice (SC) data including the choice between an EV and an ICV. The probability that individual n chooses alternative k is given by the typical MNL model:

$$P_n(k) = \frac{\exp(ASC_k + \beta_x' \cdot x_{kn})}{\sum_{j \in C_n} \exp(ASC_j + \beta_x' \cdot x_{jn})}, \tag{14}$$

where x_{jn} is a vector of vehicle attributes (including charging options for EVs), β_x is a vector of coefficients associated with the above variables and ASC_j are the typical alternative-specific constants. C_n is the choice set available to each individual n.

Data was available from a survey performed in Denmark in 2012 and 2013. Respondents who answered the survey were all participants in demonstration project where they were given an EV to use in the household for a period of three months. In order to measure any change in preferences caused by the experience with the EV, the same SC experiment was performed before and after this period. The attributes used in the SC experiment included purchase price, driving distance, driving costs (represented by fuel or electricity costs), driving performance (defined as top speed), environmental performance (defined as carbon emissions), charging options and battery lifetime for the EV. A detailed description of the survey is reported in Jensen et al. (2014).

For the purpose of this paper we used the parameters estimated jointly with both data collected before and after the direct experience with EV. From the model estimation we found that individual preferences indeed changed for some attributes after experience with the EV, and it is interesting to test this effect in forecasting. Details on the models estimated can be found in Jensen and Cherchi (2014). We believe that based on more experience about how the EV actually fits into the household, respondents choices should be more likely to represent an actual decision process. Table 1 reports the values of the estimated coefficients used in this paper.

Table 1: Model parameters of the discrete choice model

		Before		After	
	Unit	Value	Robust t-test	Value	Robust t-test
ASC (α), EV		-0.177	-0.15	-3.77	-2.24
Standard deviation for panel effect (σ), EV		1.63	8.1	1.98	7.44
Purchase price (PP)	[100,000 DKK]	-1.76	-9.85	-1.76	-9.85
Propulsion costs, EV	[DKK/km]	-6.36	-4.81	-5.2	-3.12
Propulsion costs, ICV	[DKK/km]	-1.77	-3.43	-1.21	-1.7
Driving range EV	[km]	1.13	3.02	2.72	5.03
Driving range ICV	[km]	0.12	1.58	0.19	1.74
Carbon dioxide emissions, EV	[g/km]	0.14	0.32	-0.39	-0.69
Carbon dioxide emissions, ICV	[g/km]	-0.12	-0.33	0.15	0.36
Battery stations	[units]	0.46	1.99	1.19	4.02
Public charging, slow, shop	[dummy]	0.23	0.83	0.26	0.76
Public charging, slow, city	[dummy]	-0.003	-0.01	0.71	2
Public charging, fast, shop	[dummy]	0.51	1.92	0.65	1.76
Public charging, fast, city	[dummy]	0.35	1.23	0.47	1.19
Scale				0.9	1.26[T]
Number of observations		1322		1344	
Number of individuals		290		290	
Number of parameters = 28					
Log likelihood = -1219					
Null Log likelihood = -1848					
$\bar{\rho}^2$ = 0.325					

4.3 DATA ON THE MARKET SHARES

As discussed in section 2.2, the coefficients of the diffusion model can be estimated on historical data for a similar product (if data for the new product is not available). Finding a similar innovation, however, can be challenging. Kurani et al. (1994) compare the introduction of EVs to the car market with the introduction of microwave ovens to the oven market. In the beginning, consumers had concerns about taste and health, which caused a slow penetration. Eventually, however, consumers discovered that the microwave was not a replacement for the conventional oven but rather a supplement with some new useful options, and market penetration increased from 15% in 1980 to 75-80% by 1992 (Kerin et al. 2003). Both the EV and the microwave are "high learning products", in the sense that to fully use their qualities individuals have to make behavioural adjustments (Gärling & Thøgersen 2001). We considered the possibility of applying this method. However, we questioned whether households would really consider the EV as a supplement to the conventional car in Denmark, where only 60% of households own a car and 76% of those who own a car only have one car. Moreover, the latest generations of EVs are much improved in terms of size, comfort and driving performance so that the attributes, with the exception of driving range, are now more comparable with those of a conventional car.

In this paper we used information about revealed demand obtained from Denmark. However we collected also data about the EV market share in Norway and the Netherlands, and performed several tests using these data from similar contexts. For all three countries, the number of registrations (i.e. stock data), were available on an annual basis: from 1993 to 2013 for Denmark and from 2008 to 2013 for the Netherlands and Norway. Furthermore, monthly new car registrations were available for Norway and Denmark from 2008 to 2013. Norway is the country with the highest share of EVs in Europe and is quickly reaching a share of total registrations of 1%. The development in cumulative sales for Norway and Denmark is shown in Figure 1. Even though the total car market is actually larger in Denmark (182,000 new car registrations in 2013) compared to Norway (142,000 new car registrations in 2013), the number of EV registrations is much larger in Norway compared to Denmark.

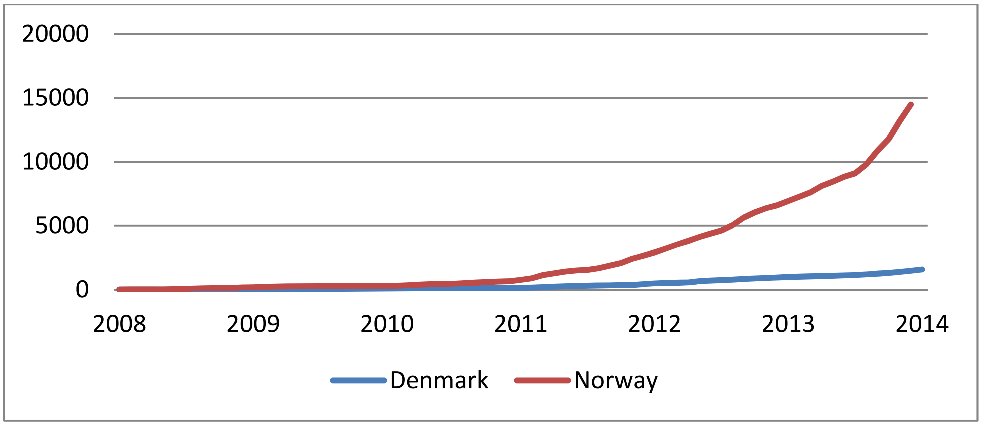

Figure 1: Cumulative sales of EVs in Norway and Denmark from 2008 to 2014[2]

[2] Data from Norway was available from Opplysningsrådet for Veitrafikken AS (Norwegian Information Comittee for Road Traffic). Data from Denmark was avaiable from The Danish Car Importers Association.

4.4 SCENARIOS FOR FORECASTING AND SIMULATION

When making predictions it is necessary to make some assumptions about the development of the different factors included in the model. With the of showing the effect of the assumptions made in forecasting (i.e. ASC and scale re-calibration and the effect of diffusion), we set up only simple scenarios, where the EV experienced most improvements due to technological development. We set up scenarios so that improvements would produce a major increase in EV market shares if only the effects of the choice model were considered. The attribute values assumed to forecast the choice model are shown in Table 2.[3]

An important issue in predicting market shares is to define the relevant aggregate population. In this application we used a simple naïve aggregation. Despite the possible aggregation bias it allowed us to show the effect of the diffusion in forecasting. However, we plan to extend this work using sample enumeration to simulate the market share based on the estimation sample.

To model the time of the initial purchase, we used monthly sales data of EVs in Denmark from January 2008 to January 2014 (both included). The sales data are for private and company registrations of personal cars, but do not include the cars registered for the demonstration project mentioned earlier (this included 195 EVs, which is a large share of the EV car registrations so far). We currently have data available from January 2005, but this was before the first full factory-made EVs were available on the Danish market, and in the period before 2008, only six EVs were sold.

Table 2: Scenarios for the forecasting model from 2008 to 2020

	Carbon		**Purchase price**		**Fuel costs**		**Driving range**		**slow city**	**slow shop**	**fast city**	**fast shop**	**Battery swap**
year	GAS	EV	GAS	EV	GAS	EV	GAS	EV	EV	EV	EV	EV	EV
	[DKK]	[DKK]	[DKK]	[DKK]	[DKK /km]	[DKK /km]	[km]	[km]	[%]	[%]	[%]	[%]	[items]
2008	1.33	0.67	154,000	240,000	0.63	0.26	800	100	0.00	0.00	0.00	0.00	0.00
2009	1.29	0.72	154,000	240,000	0.62	0.26	800	150	0.01	0.01	0.00	0.00	0
2010	1.19	0.67	154,000	230,000	0.62	0.26	800	150	0.01	0.01	0.00	0.00	0
2011	1.19	0.56	154,000	230,000	0.61	0.26	800	150	0.01	0.02	0.00	0.01	5
2012	1.19	0.45	154,000	230,000	0.60	0.26	800	150	0.05	0.05	0.01	0.03	17
2013	1.19	0.43	154,000	230,000	0.60	0.25	800	150	0.06	0.06	0.04	0.04	0
2014	1.19	0.41	152,756	225,000	0.59	0.25	800	155	0.12	0.12	0.10	0.10	0
2015	1.19	0.38	152,110	222,500	0.58	0.25	800	160	0.17	0.17	0.16	0.16	0
2016	1.19	0.36	151,457	220,000	0.57	0.25	800	176	0.23	0.23	0.21	0.21	0
2017	1.18	0.33	150,796	217,500	0.56	0.24	800	192	0.28	0.28	0.27	0.27	0
2018	1.17	0.31	150,127	215,000	0.56	0.24	800	208	0.34	0.34	0.32	0.32	0
2019	1.15	0.29	149,451	211,950	0.55	0.24	800	208	0.39	0.39	0.38	0.38	0
2020	1.14	0.26	148,766	185,995	0.54	0.24	800	208	0.45	0.45	0.44	0.44	0

[3] The attributes for the choice model forecast and the historical data are based on the following sources: European Centre for Mobility Documentation, Danish EV alliance, Norwegian Information Council for Road Traffic and Clever A/S.

5 RESULTS

In this section we present and compare the results (i.e. prediction of EV demand) obtained by applying the methodologies described in section 2. In particular, we compare the following methods: (1) use DCM estimated in the base year (2013) with the SC data; (2) use the estimated DCM but re-calibrating the ASC based on revealed aggregate sales data in Denmark 2013; (3) the joint choice/diffusion model.

5.1 PREDICTIONS USING ONLY THE DISCRETE CHOICE MODELS

In the first method we predict the demand for the 2013 and 2020 scenarios simply using all the estimated parameters (including the ASC for the EV). As shown in Table 3, the market share increases from 27% to 69% due to the assumed improvements of the attributes (as reported in Table 2). As expected, the predicted market in 2013 is far above the revealed market share for the Danish market. This is in line with the findings of (Brownstone et al. 2000), where the market share for EVs were reduced when SP data was jointly estimated with revealed preference data.

Table 3: Market share prediction examples

	Before experience		After experience	
Choice model only	2013	2020	2013	2020
No calibration	0.27	0.69	0.05	0.55
Calibration	0.003	0.04	0.003	0.07

In the second method, we adjusted the ASC to reproduce the revealed market share in 2013, based on the new car registration data from Denmark. We adjusted the ASC in the model so that it simulated the market share of 0.3% in 2013. This method is quite restrictive because the current market is very low and not fully explained by the current EV characteristics. Consequently the ASC re-calibrated to match the current market share accounts for a very big proportion of the unexplained phenomenon. When this model is used in forecast the EV market is kept at a very low level, and even with quite large improvements in the attribute values, only a 4% market share is reached in 2020. Table 3 shows the same simulation based on the parameters estimated on the “after data” (i.e. after respondents have experience with EVs). Interestingly, these parameters (without re-calibrating the ASC) seem to give a more realistic picture of the current market share as the model now predicts a market share of 5% without calibration, but also a high demand in forecast. However, if the ASC is re-calibrated to match the current market share, the model estimated using the data “after” trying the EV, still seems quite restrictive (not too different from the model estimated with the “before data”) as only a 7% market share is forecasted for 2020.

Both examples above suggest that there are time-dependent factors not included in the model. As discussed earlier, the ASC should represent all unobserved factors, but an important unobserved factor that is not considered is the diffusion process, which was still at an early stage in 2013.

5.2 PREDICTIONS ACCOUNTING FOR DIFFUSION

Assuming that the number of EV sales in a time period is equal to the number of EV adopters in that period, we first use the Bass model to explain the diffusion of EVs in Denmark. Hence equation (4) becomes:

$$S_t = \left(p + q\frac{Y_{t-1}}{M}\right)(M - Y_{t-1}) \quad (15)$$

Estimating the Bass model on the monthly sales data from Denmark between 2008 and 2013 (both inclusive), we obtained the following parameters using non-linear least squares estimation:

Table 4: Parameter estimates of the Bass model

		95% confidence interval	
Parameter	Value	Min	Max
m	22962	-296539	342463
p	0.0002	-0.0023	0.0026
q	0.0475	0.0073	0.0876
F value	37.99		
Pr>F	<.0001		

Only the parameter for imitation is significant, but we did not expect otherwise. The parameter for innovators has been low and insignificant for all tests done. We also estimated the model using the data from the Netherlands and Norway, which currently has the highest EV share of car registrations in Europe, but we did not find significant improvement compared to the Danish case. The results also emphasise that it is difficult to estimate the parameter *m* given the very low market share. As discussed in Lilien *et al.* (1999), when using non-linear least squares estimation, the estimates of m are often too low. Thus, it is often preferable to use exogenous data on *m* rather than having it as a part of the estimation procedure.

Based on these parameter estimates, a Bass model was simulated to illustrate the prediction based only on the diffusion model. We set p to zero and used the maximum value of m, as it seems plausible that in the long run there will be at least 340,000 cumulative EV sales in Denmark (around 17% of the total stock as of January 2014). To indicate the uncertainty of the model, we also calculated the number of sales for the minimum and maximum values of q. The results are shown in Figure 2.

In the low diffusion scenario, only 50 EVs are sold per month in 2020, whereas in the high diffusion scenario around 7500 EVs are sold each month. The latter corresponds to approximately 50% of the new car sales of January 2014. Clearly, the uncertainty is very high, but as also indicated in Figure 1, the estimation is based on a very low number of actual EV sales from 2008 to 2013.

The diffusion models as such are single product models and, hence, implicitly consider EVs to be a one category product that does not change over the years. In the following section we combine a diffusion model with a choice model, to take into account that the characteristics of the EV and its competitors are not constant.

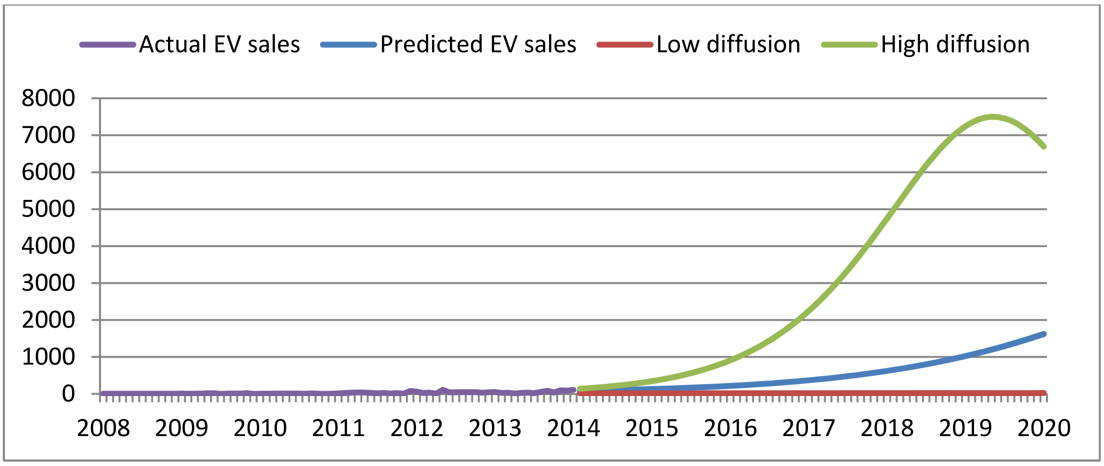

Figure 2: Monthly number of initial EV purchases

5.3 PREDICTION ACCOUNTING FOR CHOICE AND DIFFUSION

The joint diffusion and choice model presented in equation (11) was estimated on the same data as before. For the diffusion variable (i.e. number of months after market introduction), we found that a better fit was obtained if we used a log transformation, which means that the marginal effect of diffusion reduces in later time periods. For the choice model, we use the parameters presented in Table 1 and the aggregate attribute values for each year presented in Table 2. As it was not possible to estimate the parameter M, we used the maximum value estimated in the Bass model, i.e. 342,000. Then we obtained the parameters for the before and the after data shown in Table 5 respectively.

Table 5: Parameter estimates of the diffusion choice model

	Before			**After**		
		95% confidence interval			95% confidence interval	
Parameter	**Value**	**Min**	**Max**	**Value**	**Min**	**Max**
ASC^{EV}	-12.70	-17.30	-8.11	-18.51	-21.66	-15.36
q^{EV}	1.31	0.90	2.55	1.52	1.12	2.72
λ	3.37	1.42	5.32	1.88	0.79	2.97
F value	74.94			75.88		
Pr>F	<.0001			<.0001		

For this model, all the estimated parameters were significant at the 95% level (i.e. the 95% confidence interval does not include 0) but with some large confidence intervals. As already seen in the previous Bass model, the diffusion effect is difficult to estimate as the market is still very small. When simulating the model with the parameters estimated above, we found that the market was - of course - dependent on the diffusion parameter. We then performed a sensitivity test. If we set the diffusion parameter to the lowest value in the confidence interval, we obtained a market share of 8% for both the before and the after parameters. If, instead, we increased the diffusion effect to be between the minimum and the estimated value (we used the minimum + 1/5 of the confidence interval), we obtained 35% and 34% respectively. Although results are sensitive to the diffusion parameter, this example and the results reported in Figure 3, clearly show that taking into account the effect of diffusion allows for predicting a more realistic EV penetration over time.

Figure 3 shows the prediction results obtained (*i*) using the DCM without (*Uncalibrated*) and with (*Calibrated)* re-calibrating the ASC to match the base year market shares; (ii) using the joint substitution/diffusion model (*Joint*). Furthermore, letter A indicates that coefficients estimated in the before data were used, and letter B indicates that coefficients estimated in the after data were used. Results from the *Joint* models allow explaining the very low market share in the initial stage and a later and quick increase of market share once the product becomes more familiar and available in the population. At the same time, the method proposed in this paper (i.e. integrating the diffusion effect with a more detailed substitution model) also allows us to take into account the effect of improvement in the EV characteristics. This is highly relevant in the EV market because technology is still under development.

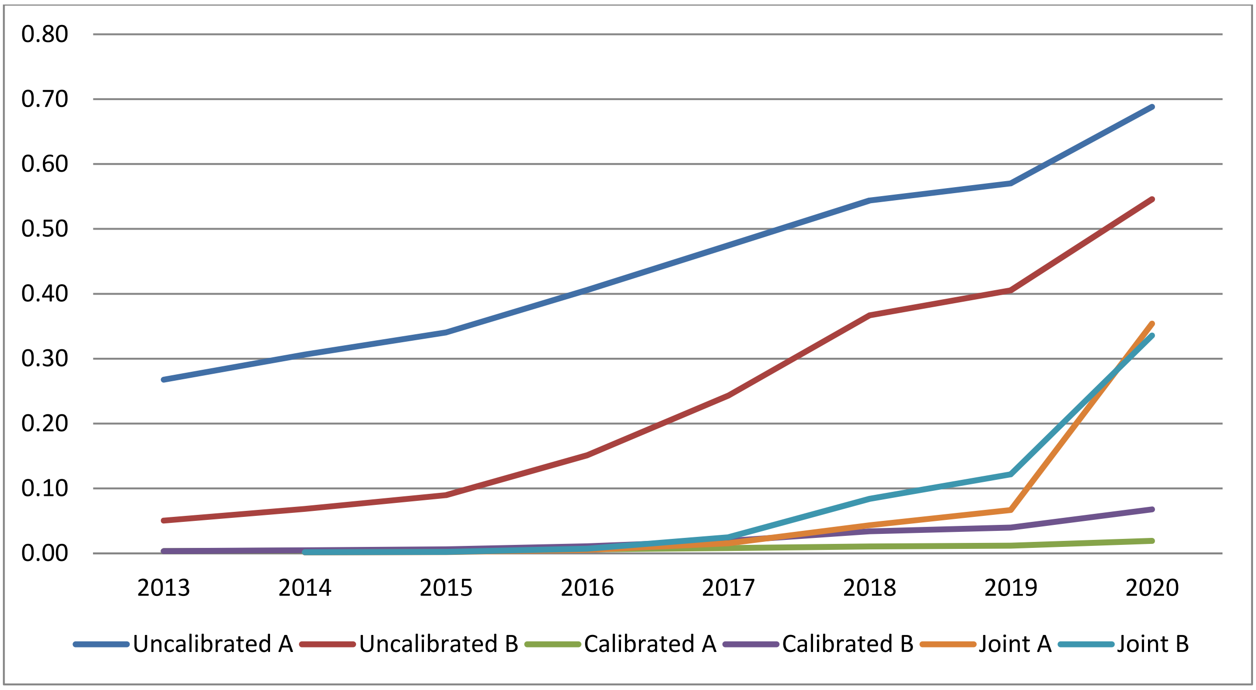

Figure 3: Predicted market shares for the different methods

6 CONCLUSION

The paper proposes a method to forecast EV demand using stated preference data and account for the diffusion effect of a new product. Using choice models to simulate the EV market share is problematic, because the current market share used to recalibrate the model in the base year is very low. This means that despite major improvements of the EV attributes, a low market share is obtained in prediction. One of the reasons for this problem is that the typical choice models do not account for the effect of diffusion, which is particularly relevant in the case of new products, such as EVs.

In this paper we suggest a method which combines choice models estimated at the disaggregate level with diffusion models to take into account jointly that new products often need time to obtain a significant market share, and that their demand is also strongly affected by the characteristics of the new product. The method we suggest allows the improvements of EV attributes not to be overshadowed by the effect of the alternative specific constants which adjust the model to the low demand of the early market.

Our results show that taking the effect of diffusion into account allows for predicting a more realistic EV penetration over time. It allows for explaining the very low market share at the initial stage and a later more rapid increase in the market share, once the product becomes more familiar and available to the population. At the same time, the method proposed in this paper also allows to take into account the effect of improvements in EV characteristics. This is highly relevant in the EV market because the technology is still under development.

Finally, our results show that a model estimated after individuals had real-life experience with electric vehicles produces what appear to be more reasonable aggregate market shares, especially for the base year. This result probably depends on our specific data and cannot be generalised. However, these results are interesting and confirm that results can of course be very different if the estimated individual preferences are different from what is typically measured from individuals without experience. The results also suggest that probably individual preferences will change over the year as individuals gain more experience with EVs. However, with the data we have at hand, it is not possible to foresee at what point in time in the future this would happen and how to incorporate this effect properly into the joint discrete/diffusion model.

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