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MODELLING REAL CHOICES BETWEEN CONVENTIONAL AND ELECTRIC CARS FOR HOME-BASED JOURNEYS

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Abstrakt
Over the last decades, several studies have focused on understanding what drives the demand for electric vehicles (EVs) and to what extent the difference in several characteristics – especially the limited driving range and limited charging options - makes it a feasible transport alternative compared to conventional internal combustion engine vehicles (ICVs). However such studies do not reveal to what extent households would actually use an EV for travel if they had the choice. We utilize a dataset describing household travel with either a private ICV or an EV that was available to the household for three months in connection with a large-scale EV demonstration project in Denmark. These data allow us to study what factors that influence the choice between an EV and an ICV for home-based journeys. The results show that several factors related to the time, length and number of trip legs affect the choice of the EV. Furthermore, we show that whether it is necessary to recharge the battery during the journey as well as the weather at the time of departure has an effect.

Introduction
A large range of studies analyse the potential use of EVs for everyday mobility in households, based on data on ICV journeys from national travel surveys (Hjorthol et al. 2014; Christensen et al. 2010). Greaves et al. (2014) used a model for energy consumption and recharging to assess the extent to which current conventional car journeys measured with GPS could be met by an EV. All studies above found that a large share of the revealed journeys are short journeys that potentially could be conducted with an EV. However such studies do not reveal to what extent households would actually use an EV for travel when they have the choice. This is relevant as the choice between an EV and an ICV may not be always in favour of an EV as several travel conditions may also influence the choice between these vehicle options.

One approach to analyse what vehicle type would be preferred applies Total Cost of Ownership (TCO) models. This approach uses travel surveys or GPS data (e.g. Plötz et al. 2014) to calculate the lowest cost for a range of alternatives over some period of time. While costs are certainly important variables to consider, there are still other factors that should be considered when studying the potential of EVs. The literature contains a large number of consumer choice studies, where it has been shown that a number of factors, e.g. purchase price, driving range, and charging infrastructure has an effect on individuals stated preferences for EVs (see e.g. Mabit & Fosgerau 2011; Potoglou & Kanaroglou 2007; Bunch et al. 1993). Several of the most recent EV choice studies furthermore account for latent attitudes that affect individual choice, such as environmental concern or a general interest in car features (see e.g. Jensen et al. 2014; Glerum et al. 2014; Bolduc et al. 2008). The data used in EV choice studies are most often based on hypothetical stated preference experiments due to limited number of actual EV choices as the product still has a very small market share. This means that the observed preferences are those of individuals with little or no experience.

Personal vehicle trials can provide detailed information about EV usage, including distance driven, location, charging activity, and driving behaviour. Data are collected by monitoring households driving an EV in their usual conditions over an extended period of time. If complemented with survey data, such as household information, travel diaries and preference experiments, such research hold a great potential in assessing consumer preferences. Of course this is a quite expensive way to gather information and hence the number of such studies is few. Golob & Gould (1998) use such a trial to assess the changes in daily vehicle miles travelled if households were using an EV instead of an ICV. They conclude that for everyday trip making, excluding infrequent long trips, a two-passenger EV with a 100 miles range requiring overnight recharging at home would be used 88% as much as the ICV it would replace. As with the previously mentioned studies, they found that most households would be able to meet their mobility needs with an EV most of the time, but even with EV experience, the trial participants kept an expectation that vehicles should have a driving range better than what the EV could satisfy. Based on questions about attitudes and purchase intentions for eight families who participated in a three month EV trial, Gärling & Johansson (1998) measure a "somewhat" reduced willingness to purchase an EV as the households obtain more experience with the EV. Among the most often given reasons for this were driving range, purchase price and recharging time. More recently, a vehicle trial in Berlin (Franke et al. 2012; Franke & Krems 2013) with 79 participant found that purchase intentions decreased from 64% to 51% after the trial, but the minimum acceptable driving range decreased significantly from 145km to 136km. When assessing the participants view on advantages and barriers (see Bühler et al. 2014) the authors found that the most mentioned EV advantages were environmental friendliness, usage of alternative energy sources for mobility, low noise emission and driving experience. The most mentioned EV barriers were limited driving range, purchase costs and charging. When assessing the effect of experience they found a significant increase in participants who mentioned driving experience, low refuelling costs, and ability to charge at home as advantages but also an increase (however only significant at 90%) in participants who mentioned limited driving range as a disadvantage. However, significantly fewer mentioned long charging duration as a disadvantage. Where the above studies only measure individual's attitudes and intentions, Jensen et al. (2014) and Jensen et al. (2013) used data from a two wave (before and after a 3 months EV vehicle trial) survey interview including a stated preference experiment to analyse potential changes in attitudes towards EVs and marginal effects for driving range, costs and charging options as EV users obtain more experience. Jensen et al. (2014) found that the sample obtained a more positive view on the driving performance of the EVs but on the other hand the sample obtained a more pessimistic view on the EVs ability to fulfil everyday mobility needs which overall meant a lower preference for the EV. The choice model representing a customised future car purchase situation presented in Jensen et al. (2013) demonstrates this effect with a negative alternative specific constant for the experienced sample and a much higher marginal effect for driving range.

Here we advance the research on the use of EVs through an analysis of what factors that are important in the choice between an EV and an ICV for journeys in households that in a period of three months had access to both vehicle types. This allows us to make a more complete analysis of marginal effects of the most relevant attributes for the household's car journeys. Furthermore, as the data collection for both car alternatives took place over an extended period of time, it is possible to investigate potential changes in marginal effects over time. To be more specific the questions we would like to answer are: What are the factors that influence the choice between an EV and an ICV for home-based journeys? And how are the effects of these factors influenced by more experience with an EV?

Data

We utilize a dataset describing household travel with either a private ICV or an EV that was available to the household for three months in connection with a large-scale EV vehicle trial in Denmark from 2011 to 2014. Each of a total of 198 EVs was distributed to several households over a period of three years, i.e. when a three month trial period finished in one household, the car was distributed to the next household. The sample of households was based on voluntary participation, but the household needed to already own at least one car and have a dedicated parking space where the EV can be charged with a home charging station from which data was also collected. Furthermore, the participating household should belong to one of the 27 participating municipalities. From those who successfully fulfilled these criteria, the project managers selected the test households based on age, gender, demography, level of education, profession and driving needs, with the clear intention of representing a broad range of the Danish population. Note that the data used for the analysis in this paper only covers the journeys conducted in 2012 and 2013 of which approximately 2/3 of the journeys are conducted in 2013[1].

In the trial period, the household had access to both their own ICV and the EV, but they were encouraged to use the EV as the primary car. All EV trips were logged during the full three months where the household was participating in the trial. For some of the households, the ICV trips were logged with a GPS device one month before and one month after the EV was received. The raw GPS data was first used to generate single trips for each of the alternatives. We then merged the single trips into complete home-based journeys. Major issues with a large share of the single trip journeys (i.e. beginning and ending at home) were detected so all of these (7380 trips) were not used. Furthermore, it was not possible to merge all trips into complete home-based journeys, so it was furthermore necessary to take out 1213 incomplete journeys. The total data set then amounts to 59789 EV journeys from 567 different households and 4298 ICV journeys from 100 households.

In the following we only consider the remaining journeys conducted by the 100 households where the ICV trips were detected, for comparison. This leaves us with 9821 EV journeys and 4298 ICV journeys. For the description and the analysis of the data we define period 1 as the month before the EV was received by the household (i.e. only ICV is available and trips are registered), period 2 as the first month after the EV was received (i.e. both ICV and EV are available and trips from both alternatives are registered) whereas period 3 is defined as the last two months where the EV was available (i.e. both alternatives were available but only the EV trips were registered). Table 1gives an overview of the number of journeys in each period classified on the two alternatives.

[1] The reason for having more observations in 2013 is that the project in the beginning had severe trouble procuring enough EVs from the suppliers.

Table 1: Number of journeys in each period (number of households in brackets)
Italic are the number of journeys conducted within the same day included in the total number

Choice	Period 1	2	3	Total
ICV	2814 (100)	1484 (96)	0	4298 (100)
	2630 (100)	*1340 (94)*	*0*	*3970 (100)*
EV	0	3747 (98)	6074 (95)	9821 (98)
	0	*3594 (98)*	*5839 (94)*	*9433 (98)*
Total	2814 (100)	5231 (100)	6074 (95)	14119 (100)
	2630 (100)	*4934 (100)*	*5839 (94)*	*13403 (100)*

The journeys conducted in period 1 should give a good indication about the travel needs of the households in the trial. On average, the daily distance travelled in the conventional car is 41.6km, which is slightly below the national average in 2013 which based on numbers from Statistics Denmark is 43.5km. This difference might represent a selection bias as it is highly possible that households took into account the short driving range of an EV before applying to the project.

In order to analyse how the extra car in the household affects the travel in the household, for each period we calculated the average number of journeys per day, the average number of trips per day, the average number of kilometres per day and the share of days where each car was used. To be able to analyse difference between weekdays and weekends we calculated different means for these. Furthermore, we split period 2 so that period 2.1 is the first two weeks of period 2 and period 2.2 is the remaining part of period 2. This description of the data is found in Figure 1.

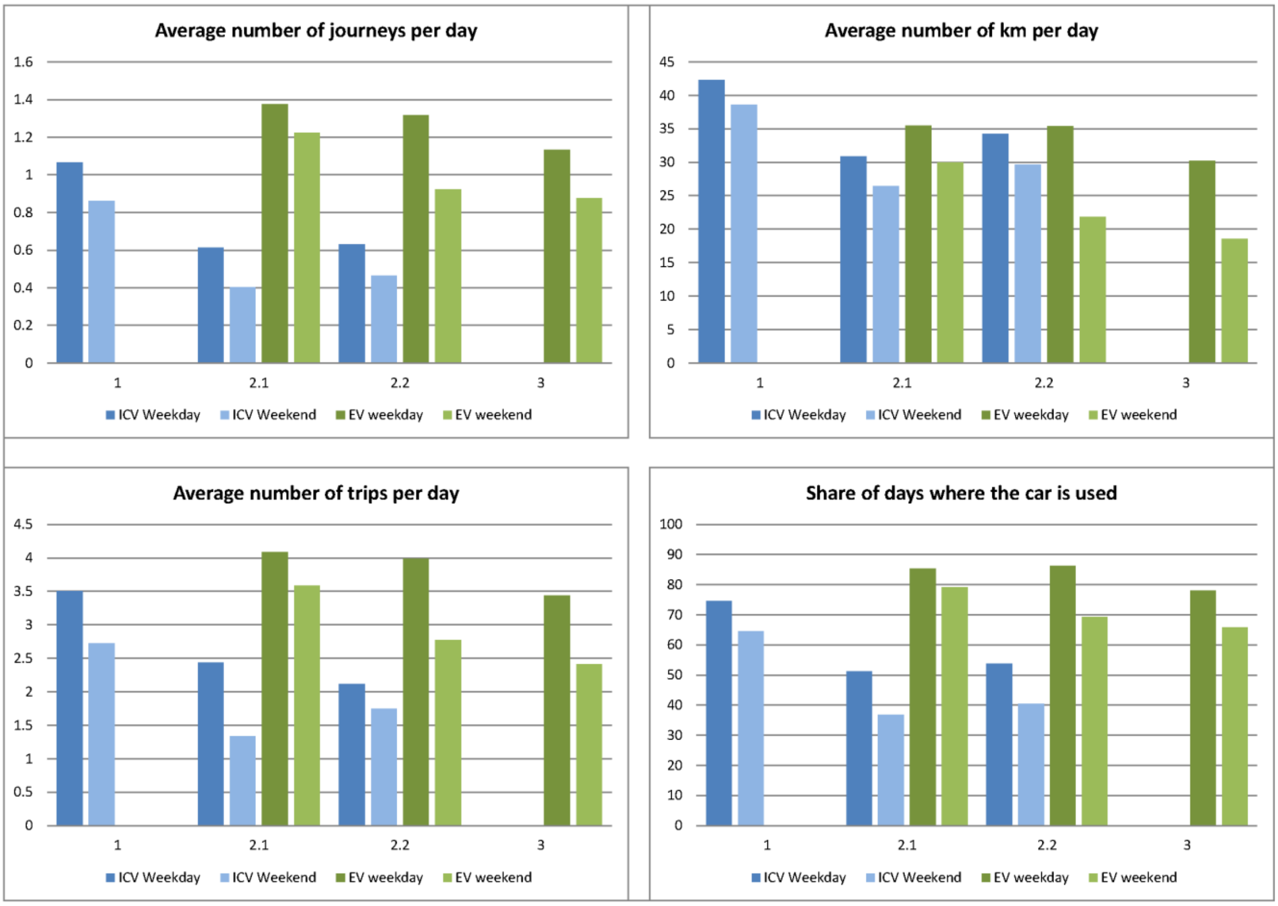

Figure 1: Descriptive statistics for the household travel in each period

It is seen that, as expected, the number of journeys in the ICV decreases when the EV becomes available. However, it is clear that the households still use the ICV for a large share of their journeys. In fact, the total household travel seem to increase drastically, which means that the households utilize the extra mobility that an extra car in the household offers. In general there is more travel on weekdays compared to weekends. The number of EV journeys in period 2 is higher than the number of ICV journeys, but as the number of kilometres driven is about the same, this indicates that the ICV is used for longer trips. Initially the number of EV journeys and the number of days where the EV is used is higher than the comparable numbers for the ICV in period 1, but with time it seems that both in terms of number of trips and in terms of kilometres, the EV usage decreases. One reason for this could be that many households in the beginning make presentation journeys to show and give trials to friends and family. Unfortunately we do not have information on the journey types, so that this can be analysed further. However, Golob & Gould (1998) report that for their EV trial including households in Southern California, such journeys accounted for approximately 11% of the total number of trips in a two week trail and that correcting for the days where such trips have been conducted reduces the daily vehicle km travelled from 64.5km to 62.6km.

Beside the GPS data for the household trips, the sources of data used in this study includes background data for each household and weather data from the locations where the trips took place. The background data were collected by the EV infrastructure provider, Clever, as a part of the application process to participate in the demonstration project. Unfortunately, most of this information describes the person in the household who made the application and not the household as such. Therefore, the only relevant information from this source is home address, number of driving licenses, the EV car model, and information about the time period where the household participated in the demonstration project. Weather data was provided by the Danish Meteorological Institute and includes hourly averages for sunshine, precipitation, wind speed and air temperature measured by weather stations covering all of Denmark. For each journey, data from the weather station nearest the starting position of the journey was used.

Method

In principle, a household member who was going to use a car in the period where the EV was available had the choice between the EV and the ICV. Hence, the model attempts to describe the situation where an individual in the household is at home and need to conduct a journey. Based on the characteristics of the household, the desired journey and the weather at the time and in the area where the decision takes place, the individual makes a choice between the EV and the ICV.

In order to model this choice, we set up a discrete choice model. Define U_{jnt} to be the utility that each individual *n* associates to alternative *j*, in the choice situation *t*. The discrete choice model can then be written as:

$$U_{jnt} = ASC_j + \boldsymbol{\beta}_j^S \boldsymbol{S}_n + \boldsymbol{\beta}_j^X \boldsymbol{X}_{jnt} + \mu_{jn} + \varepsilon_{jnt}$$

Where $\boldsymbol{S}_n$ is a vector of household characteristics, $\boldsymbol{X}_{jnt}$ is a vector of journey attributes including weather variables, $\boldsymbol{\beta}_j^S$ and $\boldsymbol{\beta}_j^X$ are the vectors of corresponding coefficients associated with the variables and ASC_j are the alternative specific constants. μ_{jn} are error components, normally distributed across individuals whereas ε_{jnt} are random terms distributed identical and independently extreme value type 1.

A common issue when working with revealed data for discrete choice modelling is to determine the unchosen alternative or alternatives. As such, it is impossible to know the characteristics of the journey if it would have been conducted with the opposite alternative. For example, it is reasonable to believe that an EV user would decide not to conduct an otherwise relevant spontaneous detour if the remaining battery level does not allow for this. Aware of this issue, we still decided to use a quite simple methodology to create the values for the non-observed alternative. We assume that for each journey, the distance is fixed. This means that the distance will not change if the non-observed alternative was chosen. In order to calculate the remaining variables for the non-observed alternative, $x_{jd,u}$, we calculated average values for the journeys classified on alternative and specific intervals d of the distance of the journey. Hence, for each observation, we have an average value for the observed alternative $x^*_{jd,o}$ and an average value for the unobserved alternative $x^*_{jd,u}$ within the corresponding distance interval. Then for each observation, the value of the unobserved alternative was calculated as:

$$x_{jd,u} = x_{jd,o} \cdot \frac{x^*_{jd,u}}{x^*_{jd,o}}$$

Note that for the number of charging events, we simply use the average value of the unobserved alternative within the corresponding distance interval.

Results

In some cases (649 observations, about 15% of total), the household used both cars on the same time. To test whether there are differences in preferences in such situations, we split the data in two. When estimating separately on these two types of data, a Likelihood Ratio test showed that a better model is obtained if separate parameters for all attributes were estimated. Hence, there is a difference between the preferences for when an alternative is used alone and when it is used at the same time as the opposite alternative. As we in this study is interested in the choice between the alternatives for a specific journey type, we decided to exclude all overlapping journeys in the model estimation (i.e. if an EV journey is conducted at the same time as an ICV journey, both observations are taken out and vice versa).

The model was estimated using Python Biogeme (Bierlaire & Fetiarison 2009) using 1000 MLHS draws. The results of the model estimation are reported in table 2. All parameters have the expected sign but we also included parameters that were not significant at 95% level. For total journey time, net driving time and number of trip-legs, we did not find any difference in preferences between the alternatives. As expected, these all have negative signs, but it does not seem that the total journey time affects the choice between ICV and EV. We tested whether the number of necessary charges has an effect on the choice but in the end, whether it was necessary to charge or not seemed to explain the choice better. In the first week of the trial there is a higher preference for the EV compared to the rest of the trial but during weekends there is a lower preference for the EV compared to week days. The parameter for the first week interacted with the number of trip legs in each journey is positive and almost cancels out the negative preference for the number of trip-legs. This indicates that individuals do not have a preference for this factor until they reach a week of experience. The parameter for EV journey time interacted with first week is negative and significant which indicates that individuals have a lower preference for using the EV for journeys conducted over longer time in the beginning of the trial

Including information about the weather highly improved the model which we to some extent also expected. Lohse-Busch et al. (2013) found that the impact of temperature on vehicle efficiency was higher for EVs than for conventional vehicles. In fact they found a 100% increase in energy consumption for a Nissan Leaf EV, when the temperature drops to 20 degrees Fahrenheit (about -7 degrees Celsius) from 70 degrees Fahrenheit (about 21 degrees Celsius). The corresponding drop in efficiency for ICVs was only 20%. Similar results for EV efficiency are found in Zahabi et al. (2014) and Fetene et al. (2015). Inevitably, such a drop in efficiency will have a great effect on the driving distance it is possible to drive on a fully charged battery which again should have an effect on EV travel behavior. Hence, we expected that a lower temperature would have a negative effect on the EV preferences. We tested several specifications for temperature, but surprisingly we were not able to find a strong effect of temperature on the choice. Interestingly, wind speed seems to explain the preferences much better than temperature, as it seems that more individuals are avoiding the EV when there is much wind and this effect is even stronger in the first week of the trial. This might be due to the fact that the EVs available as a part of the trial were mini class cars, which probably feels less stable in strong wind. Unfortunately we do not know whether this effect would be the same if the EV would have been the same car class as the ICV in the household. Also precipitation had an effect on preferences, and here it seems that individuals have stronger preferences for the EV if there is more precipitation.

Tabel 2: Discrete choice model for the choice between ICV and EV for a household journey

Name	**Value**	**Robust t-test**	
Alternative Specific Constant, EV	4.13	8.22**	**
SIGMA_EV	1.37	8.3**	**
Total journeytime	-0.0544	-1.52	
Net drivetime	-0.0624	-2.84	**
Number of triplegs	-0.771	-3.48	**
Journey distance, km, EV	-0.00287	-0.78	
At least one charge, EV	-2.23	-5.32	**
Windspeed, m/s, EV	-0.395	-12.27	**
Precipitation, mm, EV	0.491	2.26	*
Citroën dummy, EV	0.599	2.02	*
Number of driving licences, EV	-0.348	-2.07	*
City dummy, EV	0.604	2.1	*
First week dummy, EV	1.67	3.84	**
First week * Number of triplegs, EV	0.609	2.15	*
First week * Precipitation, EV	-0.569	-2.51	*
First week * Windspeed, EV	-0.272	-4.27	**
First week * Journey time, EV	-0.0984	-2.96	*
Number of MLHS draws:	1000		
Number of estimated parameters:	17		
Final log-likelihood:	-1594.36		
rho bar wrt. 0	0.459		

* significant at 5%, ** significant at 1%

Discussion and conclusion

This paper describes the data and the choice model we use to analyse households preferences for electric vehicles (EVs) when they are used for home-based EV journeys. As far as we are aware, this study represents the first attempt to model how specific factors affects how an EV is used in common households. Our work is relevant, as many studies assume that travel behaviour of EV users can be predicted by the travel behaviour of conventional internal combustion engine vehicle (ICV) users. However, as we show, EV travel behaviour is significantly affected by several factors.

The data on the household journeys were available from a large scale EV trial in Denmark where a high number of car owning households, already owning an ICV had an EV available for a period of three months each. Even though they were told to use the EV as the primary car, we show that they still used the ICV for a large share of their journeys. As such, the modelled scenarios are very artificial as few households in reality actually do have the choice between an EV and an ICV on a day to day basis. However, the analysis gives a quite detailed picture of what factors actual EV users take into consideration when they decide to conduct a journey.

The results show that both journey characteristics as well as household characteristics have an effect on preferences for using the EV. Furthermore we show that weather has a significant effect on EV travel behaviour as wind and precipitation drastically improved the model. Even though several specifications were tested for temperature, we did not find any strong indication that temperature has an effect on the choice of alternative. This is interesting, as it has been shown that temperature has a huge effect on the distance that it is possible to drive with an EV before the battery needs to be recharged.

Finally, we show that several factors are affected as users obtain experience with the EVs. (Jensen et al. 2013) already showed that individual preferences in hypothetical car purchase situations change with experience but to our knowledge this is the first time it has been shown that for EV travel behaviour, experience also change the effect of specific journey characteristics.

We think that the model presented in this paper gives a very detailed picture of household's preferences for home-based car journeys and how these preferences change with experience. However, the data holds great potential for exploring further details of how travel behaviour change when households use an EV instead of an ICV. In our future work with this data we will use the findings from this paper and focus on more specifically on the daily vehicle usage for EVs including route choice and the distribution of trip distances.

References

Bierlaire, M. & Fetiarison, M., 2009. Estimation of discrete choice models: extending biogeme. In *Swiss Transport Research Conference (STRC),*. Ascona.

Bolduc, D., Boucher, N. & Alvarez-Daziano, R., 2008. Hybrid Choice Modeling of New Technologies for Car Choice in Canada. *Transportation Research Record*, 2082(1), pp.63–71.

Bunch et al., 1993. Demand for clean-fuel vehicles in California: a discrete-choice stated preference pilot project. *Transportation Research, Part A: Policy and Practice*, 27(3), pp.237–253.

Bühler, F. et al., 2014. Is EV experience related to EV acceptance? Results from a German field study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25, pp.34–49.

Christensen, L., Kveiborg, O. & Mabit, S.L., 2010. The Market for electric vehicles - what do potential users want. In *12th World Conference on Transportation Research*.

Fetene, G.M. et al., 2015. Harnessing Big-Data for Estimating the Energy Consumption and Driving range of Electric Vehicles. In *XIII Network on European Communications and Transport Activities Research (NECTAR) conference*.

Franke, T. et al., 2012. Enhancing sustainability of electric vehicles: A field study approach to understanding user acceptance and behavior. In L. Dorn & M. Sullman, eds. *Advances in Traffic Psychology*.

Franke, T. & Krems, J.F., 2013. What drives range preferences in electric vehicle users? *Transport Policy*, 30(1), pp.56–62.

Glerum, A. et al., 2014. Forecasting the Demand for Electric Vehicles: Accounting for Attitudes and Perceptions. *Transportation Science*, 48(4), pp.483–499.

Golob, T.F. & Gould, J., 1998. Projecting use of electric vehicles from household vehicle trials. *Transportation Research Part B: Methodological*, 32(7), pp.441–454.

Greaves, S., Backman, H. & Ellison, A.B., 2014. An empirical assessment of the feasibility of battery electric vehicles for day-to-day driving. *Transportation Research Part A: Policy and Practice*, 66(0), pp.226–237.

Gärling, A. & Johansson, A., 1998. *An EV in the family*, Chalmers University of Technology, Department of Road and Traffic Planning, Göteborg.

Hjorthol, R. et al., 2014. Everyday Mobility and Potential Use of Electric Vehicles. *TØI Report*, (1352).

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, pp.24–32.

Jensen, A.F., Cherchi, E. & Ortúzar, J. de D., 2014. A Long Panel Survey to Elicit Variation in Preferences and Attitudes in the Choice of Electric Vehicles. *Transportation*, 41(5), pp.973–993.

Lohse-Busch, H. et al., 2013. *Ambient Temperature (20 F, 72 F and 95 F) Impact on Fuel and Energy Consumption for Several Conventional Vehicles, Hybrid and Plug-In Hybrid Electric Vehicles and Battery Electric Vehicle*, SAE Technical Paper.

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

Plötz, P., Gnann, T. & Wietschel, M., 2014. Modelling market diffusion of electric vehicles with real world driving data - Part I: Model structure and validation. *Ecological Economics*, 107(0), pp.411–421.

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

Zahabi, S.A.H. et al., 2014. Fuel economy of hybrid-electric versus conventional gasoline vehicles in real-world conditions: A case study of cold cities in Quebec, Canada. *Transportation Research Part D: Transport and Environment*, 32, pp.184–192.