



## The use of electric vehicles: A case study on adding an electric car to a household

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**Highlights:**

- GPS data from a large-scale EV demonstration trial is used to analyse EV usage behaviour when both an EV and a CV is available in a household.
- The results of a mixed non-linear regression model for daily distances driven show that EV use is reduced during weekends and that only EV use is affected by weather variables.
- The results of a mixed logit model for the choice between the CV and the EV for a homebased journey show that the EV is mostly used for shorter trips during morning peaks on weekdays with less need for out-of-home charging.
- Both models indicate that the EV alternative is mostly used for well-planned transport

## **The use of electric vehicles: a case study on adding an electric car to a household**

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## **Abstract**

The market share of battery electric vehicles (EVs) is expected to increase in the near future, but so far little is known about the actual usage of this emergent technology. Consumer preference studies have indicated that the current limitation on driving distance is important. At the same time studies on the actual use of household vehicles indicate modest requirements for daily travel. An unresolved issue is to what extent these range limitations affect daily travel in EVs. In this study, we use real electric vehicle trip data to study the distribution of daily use and types of home-based journeys where a household decides to use an electric vehicle instead of their conventional vehicle. The results show how several factors related to distance and number of necessary charging events have plausible effects on electric vehicle travel behaviour. Further, the modelling indicates that the EV alternative is mostly used for well-planned transport and that EV use will not be the same as use of the conventional vehicle in two-vehicle households.

## 1. Introduction

Many governments see a greater use of battery electric vehicles (EVs) as an important way to fulfil their environmental goals. The absence of local exhaust emissions can contribute to less local air pollution, and with a higher share of renewable energy sources in the electricity production, EVs can also contribute to reducing global emissions from transport. However, the environmental impact of large-scale EV adoption is not obvious as it cannot be assumed that conventional vehicles (CVs) currently on the road are simply replaced by EVs and that individual behaviour otherwise stays the same.

Potential EV users benefit from an increasing availability of EV models with greater comfort and better driving performance. Furthermore, EVs have the potential to be cheaper to run and maintain than comparable CVs. To obtain these benefits, however, the consumer must presently accept a limited driving distance between charges and that charging time, depending on the available facilities where the car is parked, takes minimum 20 minutes for recharging up to 80% battery capacity and usually several hours to reach full capacity. As a result, there are limits to the travel that can be performed with an EV, and for many car users it would not be possible to exchange their current CV with an EV without some level of adaption in their daily way of travel. For example, commuters with more than 75 km distance to work (15% of commuting trips (TU 2015)) would have uncertainty about getting home, e.g. in cold weather after work if they use a EV with today's battery capacity. Therefore, they would need to either find charging possibilities during the day, which could include detours, or to use other transport alternatives. Both the benefits and limitations will most likely have an effect on the EV market and it is therefore very useful to know more about potential users' EV travel.

Recent decades have provided a number of studies regarding the use of EVs using different methodologies. Due to a lack of information about *actual* EV usage, many studies have instead been based on information about current usage of CVs with the assumption that car users do not change behaviour whether they use a CV or an EV. Such information has then been obtained from CV odometer readings at refuelling (see e.g. Greene 1985), from national travel surveys (see e.g. Christensen 2011), or from CV journeys measured with GPS (see e.g. Pearre et al. 2011; Greaves et al. 2014). These studies find that with the driving distances possible with the EVs currently available, a large share of the households would be able to maintain their current way of travel with only a minor level of adaption. These studies rely on simple assumptions about the effect of range limitations on usage that may be problematic. This is also indicated in the results of research from consumer choice studies on EV consumer acceptance, which show that the driving distance possible to cover on a fully charged battery is of great importance to the potential users (see e.g. Jensen et al. 2013; Dimitropoulos, Rietveld, and van Ommeren 2013; Mabit & Fosgerau 2011; Bunch et al. 1993).

The above mentioned studies on car usage base their conclusions on data from CV usage or data from hypothetical settings, which might not be representative for actual EV user behaviour. As the EV market is still quite immature in most countries, personal vehicle trials are instead often used to obtain information about EV usage, including daily distances, location, charging activity and driving behaviour. Data is then collected by monitoring households driving an EV in their usual routines over an extended period of time. Golob & Gould (1998) use such a trial to assess the changes in daily vehicle usage if households were using an EV instead of a CV. They conclude that for everyday trips, excluding infrequent long trips, a two passenger EV with a 100 mile driving range requiring overnight recharging at home would be used 88% as much as the CV it would replace in terms of daily distances. In a three month field study in Germany, Franke & Krems (2013) found that the daily distance driven in the EVs was similar to German CV users. In another 3-month field study, Jensen et al. (2014) interviewed household members before and after a three month trial with EVs and found that even though the participants with EV experience had a more positive view on the EVs driving characteristics (such as comfort and acceleration) and found charging less problematic, they

expressed a higher concern with being able to maintain their current mobility need if they had to fulfil them with an EV.

The only country in the world where the EV market is mature enough to base EV studies on revealed data from EV owning households is probably Norway. Klöckner et al. (2013) base their study on revealed data from the Norwegian Public Roads Administration (Statens Vegvesen) database and self-reported car use from private households who purchased either a CV or an EV. They show that an EV is generally used in multi-car households (In less than 10% of the EV households, this is their only car) and that the EV is used for the major share of the total amount of trips in the household, except when the purpose is holiday. Furthermore, a lower level of car use is only found for single car EV households compared to single car CV households.

In this study, we seek to answer how the current technological differences might affect households' daily vehicle use. More specifically, we analyse the factors that affect EV use in a different way than CV use and quantify how these factors affect the daily distances driven in a household where both an EV and a CV are available. EVs have some obvious limitations compared to CVs, which we hypothesise will affect several aspects of transport behaviour. For example, the limited driving range provided by a fully charged battery could affect both the distance travelled and the type of trips conducted (as in Klöckner et al., 2013). Furthermore, as it has been observed that the driving distance of EVs is highly affected by temperature (see e.g. Zahabi et al. 2014) we investigate how EV usage is affected by temperature and other weather variables. Finally, as EVs are an emerging technology, and most of the households in the trial would therefore most probably not have tried an EV before, we investigate how experience with the EV affects daily use. Previously, Franke & Krems (2013) found from their vehicle trial study that the stated acceptable minimum driving range for an EV in a purchase situation became lower for more experienced users, indicating that the users will adapt to the vehicle technology with time. However, in the stated choice experiment in Jensen et al. (2013), experienced users were seen to value driving range higher than inexperienced users. We note that even though these studies seem contradictory, the results cannot be directly compared as the first refers to absolute valuation of driving range while the latter refers to the marginal valuation.

The simplest indicator of car usage is the distance travelled in the household. Greene (1985) and Lin et al. (2012) specifically investigate the distributions of daily vehicle usage for CVs in order to study the implications for EV and hybrid electric vehicle use, respectively. They suggest the gamma distribution to be best at representing vehicle use in households, but to our knowledge, similar analyses have not been conducted on actual EV data to investigate whether the daily vehicle usage is different when using an EV compared to a CV. Another indicator of usage would be to look at individuals' decision to travel by a certain mode instead of other modes. The literature contains many mode choice studies (see e.g. Bhat 1995; Koppelman & Sethi 2005) but we are not aware of such studies particularly looking at which factors would affect the choice of EV for a trip or a journey.

We utilise data collected from participants of a large-scale EV trial conducted in Denmark in which participating households already owning a CV had access to an EV for a period of three months. With GPS data collected before and after the beginning of the trial period and in both the EV and the CV, we are able to analyse factors related to daily distances driven for both the EV and the CV. We do this by estimating and comparing the parameters of the gamma distribution as suggested in Lin et al. (2012) but in addition we also include explanatory variables describing household characteristics, type of day, and weather conditions. We advance the research on the use of EVs through an analysis of which factors are important in the choice between an EV and a CV for home-based journeys conducted by the participating households. This model allows assessment of how the share of EV journeys are affected by various explanatory variables, e.g. number of necessary charging events. This will especially be important for predictions of EV use conditional on car ownership for the next 5-15 years where EV households will probably own both CVs and EVs as indicated in a recent study (Klöckner et al. 2013). 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 behaviour when users obtain more EV experience. Based on these analyses we can investigate the assumption of previous literature that behaviour from CV use can be transferred to EV use.

The remainder of the paper is organised as follows. In section 2, we describe the data available for this study and present the methods used. In section 3, we present descriptive statistics and the results of the two models showing factors important for daily distance travelled and the choice between EV and CV for home-based journeys. Section 4 contains the discussion and concluding remarks.

## **2. Method**

### **2.1 Sample**

Travel by EVs and CVs was observed from 2011 to 2013 for 100 households in 13 different municipalities in Denmark. When an EV had been with a household for three months, it was re-distributed to another household, which meant that the trial study covered all seasons, but that each household would not. Each household already owned a CV prior to the study and data was collected for this vehicle one month before and one month after the household received an EV, which they could use as if it was their own. The households had the EV available for approximately three months and data was collected for this vehicle for all three months. All households received either a Peugeot iOn, a Citroën C-Zero or a Mitsubishi iMiEV, which are similar small sized cars with room for 4-5 persons and limited luggage. The driving range according to the European NEDC standard is for all cars 150km (Peugeot 2017), but according to Fetene et al. (2017), only 7% of the trips could achieve this distance based on the energy consumption measured. Rather, the driving distance possible was less than 90km on average. The participants did not have to pay for the EV or the installation of the charging device, but they had to pay for the electricity used during the trial. Beside being able to charge the vehicles at home, the participants had access to charging infrastructure from the Danish charging infrastructure provider, Clever, which at the time of the trial covered all of Denmark, including both 3.7kW AC chargers and 50kW DC quick chargers. With the AC chargers, it takes about 6 hours for a full recharge, whereas the DC chargers can charge up to 80% of the battery capacity within half an hour.

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 could be charged with a home charging station. This information was collected online as a part of the application process. From those who successfully fulfilled the criteria, the project managers selected the test households based on age, gender, demography and level of education, with the clear intention of representing a broad range of the Danish population. The description of the sample can be found in Table 1. Upon receiving the EV, the participating households were encouraged to use the EV as their primary car.

**Table 1: Sample description**

Variable	Unit	N	Mean	Min	Max
Age of primary respondent	years	100	45.46	25	69
Primary respondent is male	dummy	100	0.57	0	1
Number of drivers in household		100	2.08	1	4
Density in household area	pop/km <sup>2</sup>	100	12.44	0	117.93
city	dummy	100	0.09	0	1
	Group	N	share		
Household income group	Less than 160,000 DK	1	1		
	160,000-230,000 DKK	1	1		
	230,000-450,000 DKK	9	9		
	450,000-750,000 DKK	58	58		
	750,000-1,000,000 DKK	22	22		
	More than 1,000,000 DKK	9	9		
Education level of primary respondent	Primary school	5	5		
	High school	7	7		
	Skilled worker	14	14		
	Short higher education	18	18		
	Medium higher education (BA)	33	33		
	Long higher education (MA) or higher	23	23		

## 2.2. Daily distance travelled

We assume that the daily distance travelled in the available household vehicles is a stochastic variable following some distribution. For practical reasons, we require such a distribution to be non-negative, have flexible scewness and to have easy-to-estimate parameters. For a similar analysis of daily distances travelled in conventional cars, Greene (1985) suggested the gamma distribution while in a more recent study, (Lin et al. 2012) focused more specifically on validating the gamma distribution as the preferred distribution (also for travel in conventional cars) over the Weibull and the log-normal distributions. For both the conventional and the electric car alternatives, we tested these distributions and found no larger differences between them. For both datasets, the Weibull performed best with AIC<sup>1</sup> for CV and EV to be 31253 and 57148, respectively, while the corresponding statistic for the gamma distribution was 31259 and 57204 for CVs and EVs, respectively. For the log-normal distribution we obtained an AIC of 31314 for CV and 58294 for EV. As we found so small differences in fit and due to the already mentioned evidence of using the gamma distribution for similar analyses, we assume that the daily distance travelled in a household vehicle,  $y$ , follows the gamma distribution, i.e.:

$$f(y) = \frac{1}{\Gamma(v)y} \left(\frac{yv}{\mu}\right)^v \exp\left(-\frac{yv}{\mu}\right) \quad \forall 0 < y < \infty,$$

where  $\Gamma$  is the gamma function,  $v$  is a scale parameter to be estimated and  $\mu_i$  is the mean. As for other Generalized Linear Models, the mean  $\mu_i$  of the response in the  $i^{th}$  observation is related to a linear predictor through a monotonic differentiable link function,  $g$ :

$$g(\mu_{in}) = \alpha + \boldsymbol{\beta}' \mathbf{x}_i + \boldsymbol{\gamma}' \mathbf{s}_n + \omega_{in},$$

where  $\mathbf{x}_{in}$  are exogenous variables describing characteristics of the day where the distance was driven and  $\mathbf{s}_n$  are exogenous variables describing characteristics of the household using the car. Finally,  $\alpha$ ,  $\boldsymbol{\beta}$  and  $\boldsymbol{\gamma}$  are vectors of parameters to be estimated whereas  $\omega_{in}$  are error components

<sup>1</sup> Akaike Information Criterion is a relative quality measure used for model comparison.

normally distributed with mean zero and standard deviation,  $\sigma_\omega$ . With this error specification of the link function, we are able to take into account the panel effect of several observations per household. Note that in Greene (1985) and Lin et al. (2012) only  $\nu$  and  $\alpha$  is estimated and they estimate separate parameters for each household and analyse the distribution of these. With the above specification, we include several exogenous explanatory variables and as we take into account the panel effect, we can estimate general parameters across the entire dataset. The results of the estimation are presented in section 3.

### 2.3 The choice between CVs and EVs for home-based household journeys

On many occasions, a household member who was going to use a car in the period during which the EV was available had the choice between the EV and the CV. Hence, the individual makes a choice between the EV and the CV. To analyse this, we set up a discrete choice model that describes a situation in which an individual in the household is at home and needs to conduct a journey, taking into account the characteristics of the household, the desired journey, and the weather at the time in the area where the decision takes place.

More specifically, we set up a mixed logit model. Define  $U_{jnt}$  to be the utility that each individual  $n$  associates to alternative  $j$ , in the choice situation  $t$ . The model can then be written as:

$$U_{jnt} = ASC_j + \beta_j^S \mathbf{S}_n + \beta_j^X \mathbf{X}_{jnt} + \mu_{jn} + \varepsilon_{jnt}$$

where  $\mathbf{S}_n$  is a vector of household characteristics,  $\mathbf{X}_{jnt}$  is a vector of journey attributes including weather variables,  $\beta_j^S$  and  $\beta_j^X$  are the vectors of the corresponding coefficients associated with the variables, and  $ASC_j$  are the alternative specific constants. The  $\mu_{jn}$ 's are error components, normally distributed across individuals, whereas  $\varepsilon_{jnt}$  are random terms distributed identically and independently extreme value type 1.

A common issue when working with revealed data for discrete choice modelling is to determine the attributes of the unchosen alternative or alternatives. As such, it is very difficult to measure the characteristics of the journey if it had 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. Cognisant of this issue, we decided to use a 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 observed journeys classified on 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 for an unobserved EV trip, we simply use the average value of all EV trips within the corresponding distance interval.

### 3. Results

The raw GPS data was first used to generate 48284 single origin-destination trips for each of the two alternatives. We then merged the single trips into complete home-based journeys. We took out 3358 trips (7%), mainly because they were beginning and ending at home (circle trips) or in a few cases because they otherwise could not be fitted into a complete journey. The reason we took out circle trips from the sample data was that an unreasonably large share of trips were detected as circle trips, especially for the CV alternative. Looking at the data, most of the circle trips were clearly due to observation errors with many observations around the household. We did, however test the models without the filter, which did not lead to different results. The total data set after filtering and cleaning amounts to approx. 30,000 EV trips summing to 260,000km of driving and approx. 14,500 CV trips summing to 197,000km of driving.

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 a CV is available and trips are registered), period 2 as the first month after the EV was received (in which both a CV and an EV are available and trips from both alternatives are registered), and period 3 defined as the last two months where the EV was available (i.e. both alternatives were available but only the EV trips were registered).

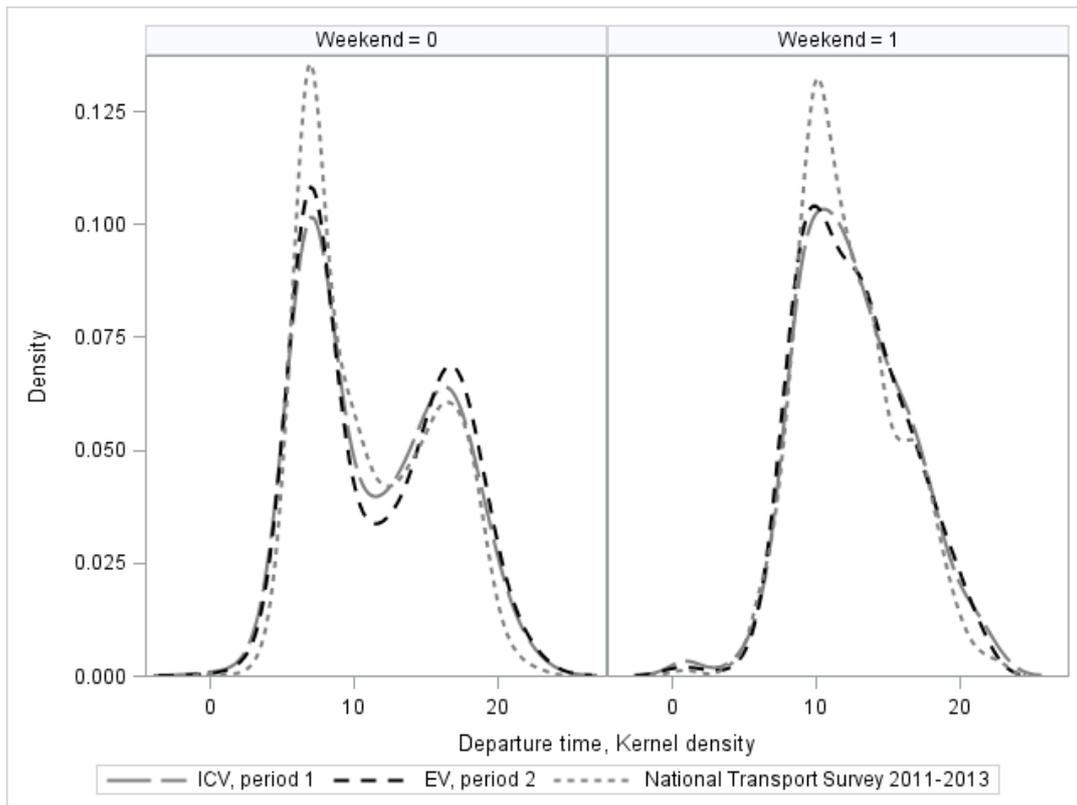
Table 2 presents summary statistics for the trips and journeys in the dataset as well as for the Danish National Travel survey (TU 2015).

Table 2: Trip and journey characteristics

Period	TU	CV		EV		Total
	2011-2013	1	2	2	3	
<b>Number of trips</b>		<b>9140</b>	<b>5433</b>	<b>11107</b>	<b>19246</b>	<b>44926</b>
<i>Average trip length [km]</i>	16.8	12.6	15.1	8.6	8.6	
<i>Average trip duration [min]</i>	17.9	13.7	15.8	11.6	11.4	
<b>Number of journeys</b>		<b>2814</b>	<b>1484</b>	<b>3747</b>	<b>6484</b>	<b>14529</b>
<i>Average journey length [km]</i>	39.9	41.0	55.1	25.9	25.2	
<i>Average journey duration [min]</i>	44.3	44.7	57.5	34.8	33.6	
<i>Average number of trips per journey</i>	3,45	3.26	3.63	3.00	2.95	
<i>Average number of charges per journey</i>				0.13	0.12	
<i>Journey conducted at the same time as other alt.</i>			23.0%	9.9%		
<i>Journey begins and ends same day</i>		93.5%	90.3%	95.9%	96.1%	

The trips conducted in the CV in period 1 should give a good indication about the travel needs of the households in the trial. The journey characteristics match very well with those of the National Travel Survey, while the trip characteristics are lower both in terms of distance and duration. It is observed that when the EV becomes available in period 2, compared to CV trips in period 1, CV trips and journeys are on average longer and take a longer time, while the EV trips and journeys are shorter and take less time. Furthermore, the number of trips per journey and number of overnight journeys becomes higher in period 2, while for EVs both of these measures are lower and remain low in period 3. Finally, we note that charging during a journey (i.e. away from home) is rare.

As already mentioned in the description of the sample, the participants were encouraged to use the EV as their primary car, but without any further restrictions or incentives. Whether these participants actually adopted the EV as their primary car or simply used it as an extra car whenever a need arose, is unknown from the data. Instead, we used information about journey departure time from home and compared with data from The National Travel Survey. It is observed in the density plots in Figure 1 that the graphs match very well across TU, CV and EV. From this we infer that, in general, the EV was actually used to accommodate the existing transport needs in the households, both during weekdays and weekends. Note that the high top of the TU data density plots is most probably due to the interview method rather than differences in behaviour across the samples<sup>2</sup>.



**Figure 1: Departure time kernel density for weekdays and weekends**

In order to analyse how the extra car in the household affects travel in the household, for each period we calculated the average number of trips per day, the average number of journeys per day, the average number of kilometres per day, and the share of days where each car was used. Note that all these averages take into account days where the cars have not been used. To be able to analyse differences 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 covers the remainder of period 2. This description of the data is found in Figure 2.

On average, the daily distance travelled in the conventional car is 41.1 km which is in the same range as the national average for the years 2011 to 2013 which was 44.8 km according to Statistics Denmark (DST 2017)<sup>3</sup>.

<sup>2</sup> In a phone or online interview as TU, respondents tend to jump to the nearest whole hour so that e.g. a departure at 7.56am would become 8.00 in TU and included in the 8-9 slot, while it should be in the 7-8 slot.

<sup>3</sup> The average from Statistics Denmark was calculated over the whole population (i.e. also households without a car) and also includes kilometres driven in vans.

As expected, it is seen that the number of journeys conducted in the CV decreases when the EV becomes available. However, it is also clear that the households still use the CV for a large share of their journeys. In fact, the total household car travel seems to increase drastically, which means that the households make use of the extra mobility that an extra car in the household offers. This highlights that effects observed in period 2 and 3 are a mixture of the extra car and the fact that the car is an EV. 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 CV journeys, while the number of kilometres driven is about the same. This indicates that the CV 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 CV 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. Possible reasons for this could be the novelty of the EV in the beginning of the trial and 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 trial and that correcting for the days where such trips were conducted, reduces the daily vehicle km travelled from 64.5 km (39.8 miles) to 62.6km (38.9 miles). Another reason could be that the EV is used for journeys that would have been conducted with other modes if the EV would not have been available.

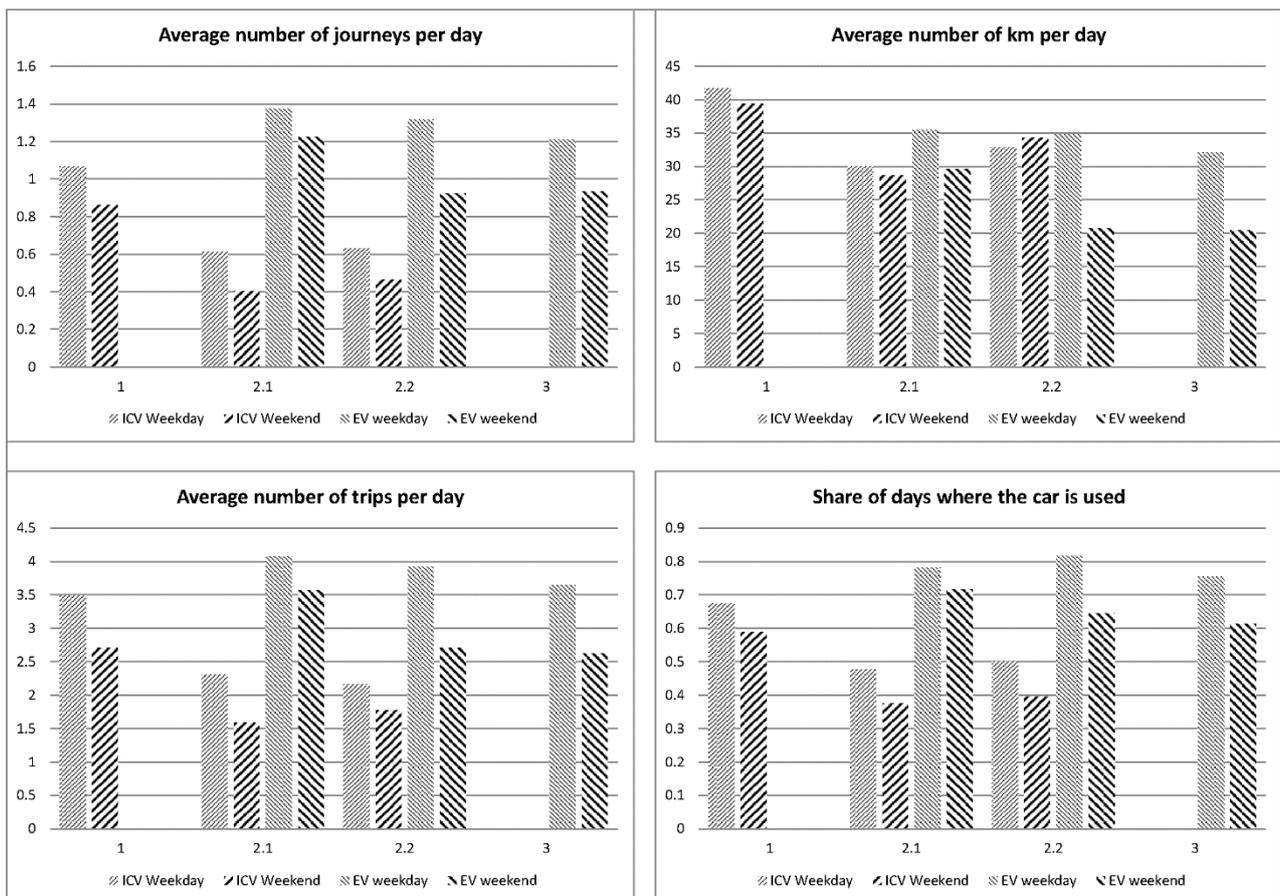


Figure 2: Descriptive statistics for the household travel in each period

Regarding the charging behaviour of the EV users, each household charged their EV 67 times on average during the test period (including charging events at home), which approximately accounts for 5.6 times per week. This is much more than the 3 times per week reported in Franke and Krems (2013b). Similar to this study, however, we found that the users typically charge their car when there is plenty of energy left in the battery. On average the state of charge (SOC) of the battery was 51% when a charge was initiated. 65% of the charges were conducted when the SOC was more than 40% (similar to 66% found in Franke and Krems (2013b)).

### **3.1 Results on daily distance travelled**

For each individual, the distances for all trips for each car alternative have been summed over the days where the car alternative was used in order to obtain the daily distance travelled (DDT). In Table 3, we present the model estimations on the DDT for both alternatives over the periods for which data is available. For CVs these are periods 1 and 2 and for EVs these are periods 2 and 3. To investigate whether there are significant differences across periods for each alternative, for each variable included, we also tested an interaction on the last relevant period.

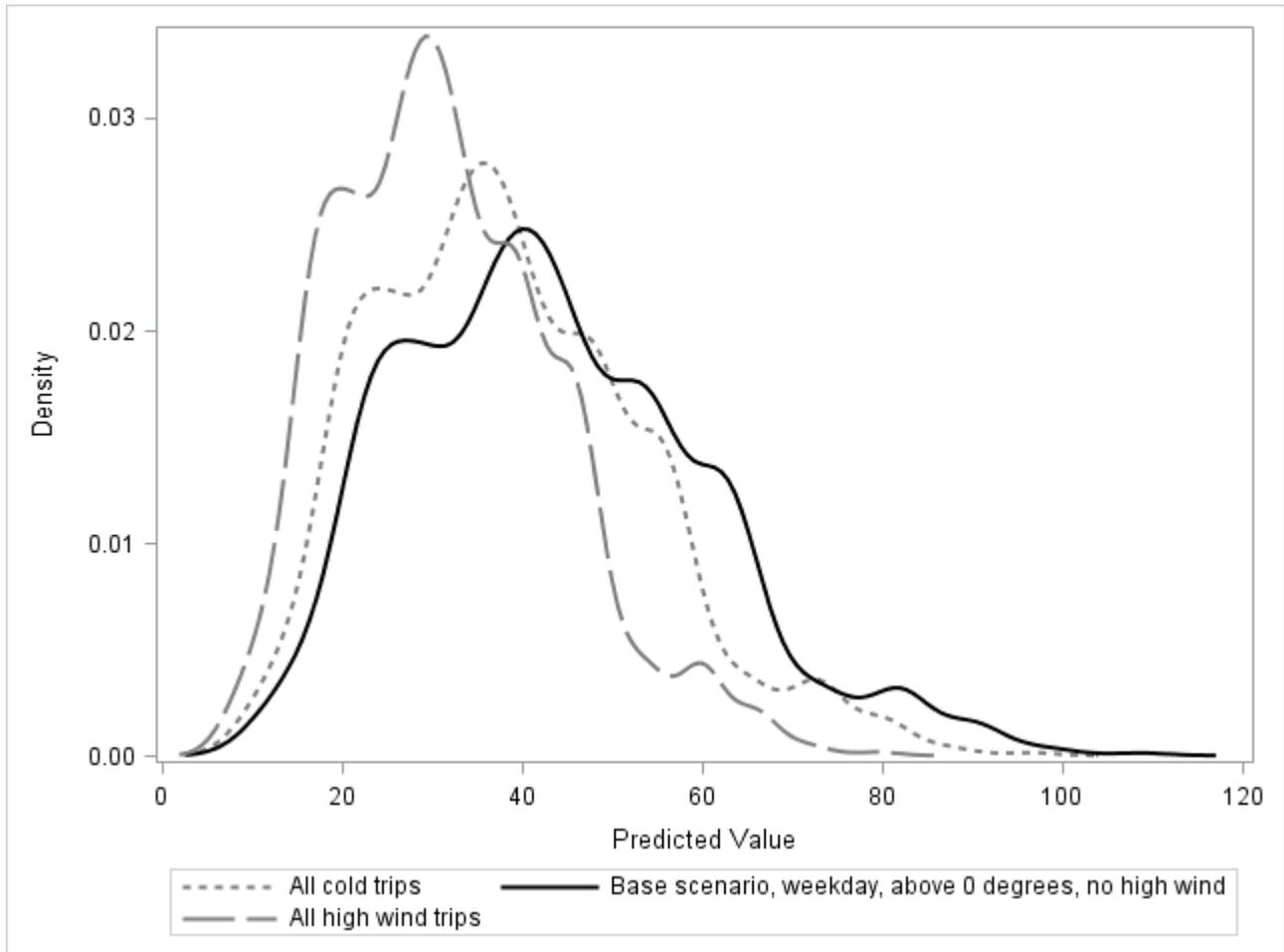
Across the model estimations for both alternatives, the scale, the intercept, and the standard deviation for the error component are highly significant. For both CVs and EVs, across all periods, population density in the area of the household has a significant and negative effect on DDT. The parameter estimates indicate some interesting differences in how the cars are used. Location in city areas has a significant and negative parameter in the model for CV use. However, such an effect was not found for EVs. A large difference in modelling results appears during weekends. In period 1, we did not find a significant difference in DDT across weekdays and weekends for CVs. The model shows however, that in period 2, the CV is used significantly more in weekends than on weekdays. For EVs, the picture is opposite. The effect is significantly higher in period 3 than period 2, which indicates that the effect is even stronger with EV experience.

**Table 3: Estimation of the mixed non-linear regression model for daily distance travelled (DDT) in CV and EV**

Alternative Periods	CV			EV		
	1+2			2+3		
	Estimate	t Value	p Value	Estimate	t Value	p Value
Variance parameter	0.13	5.4	0.00	0.14	6.45	0.00
Intercept	4.05	34.95	0.00	4.15	33.22	0.00
First week of period 2				0.12	2.53	0.01
First two weeks of period 2				0.07	1.81	0.07
Home is in a city area	-0.37	-2.56	0.01			
Population density at home	-0.01	-4.91	0.00	-0.01	-3.56	0.00
Weekend	0.04	0.85	0.40	-0.14	-3.75	0.00
Weekend * last period	0.2	2.76	0.01	-0.12	-2.76	0.01
Number of driving licenses in household	0.09	1.9	0.06	-0.1	-2.26	0.02
Avg. temp. at trip departure is below 0 degrees Celsius				-0.12	-3.55	0.00
Avg. wind speed at trip departure is higher than 10m/s				-0.31	-3.1	0.00
Electric vehicle in household is a Mitsubishi ImiEV				-0.34	-2.9	0.00
Electric vehicle in household is a Peugeot Ion				-0.21	-2.39	0.02
Scale parameter	1.15	42.95	0.00	1.74	59.62	0.00
Number of observations		3017			6094	
Number of parameters		8			13	
Data period		1+2			2+3	
Akaike information criterion (AIC)		30916			55823	
AIC/N		10.25			9.16	

The parameter for the number of driving licences in the household is positive and significant for CVs (however only at 10%) which makes sense as there are more individuals who can use the car. However, for EVs, the parameter is negative and significant which is less intuitive. This might have more to do with the behaviour related to household size than the actual number of household members with a driving license. Unfortunately, it was not possible to control for household size in this study. For CVs, none of the weather variables affect the DDT in either of the two periods. However, and as expected, high wind speeds and cold temperatures have a negative effect on the DDT for EVs. In Figure 3, we show how these weather variables with this model affect the daily distance distribution compared with a base scenario in which we assume that all trips are conducted on a weekday where the average temperature is above 0 C° and the average wind speed is below 10m/s.

We also analysed, whether there was a time effect for the weather variables so that, e.g. users with EV experience (period 3) would use the EV differently when they found out that high wind speeds and cold weather significantly reduced the driving distance of the EV. However, we did not find any such effects. Furthermore, we did not find any effects from precipitation or sunshine. Whether these effects can be seen as causal or spurious is discussed in Section 4.



**Figure 3: Density plot of the effect of weather variables on the distribution of daily distance traveled**

It would have been interesting to extend the analysis to different types of trips, allowing for e.g. filtering out trips that are related to transitory needs to present the EV to neighbours or family. This effect was instead, to some extent, taken into account by including a dummy for the first week of the trial and one for the first two weeks of the trial. According to the model, this effect is only significant for the first week and as expected the parameter sign is positive. Surprisingly, in both periods 2 and 3, we found a negative and significant effect on daily use for those households who were driving a Mitsubishi ImiEV instead of a Peugeot Ion or a Citroën Z-Cero. As these three car models are basically the same, we do not believe that this is an effect of the car as such, but a geographical effect as in most cases the different car models were not evenly distributed across municipalities. We tried to find the actual effect by including more geographical variables, but without success.

### **3.2 The choice between a CV and an EV**

The next model investigates, by means of a mixed logit model, factors relevant for the decision of using the EV or the CV for a specific journey. In some cases (about 15% of all), the household used both cars at the same time. To test whether there are differences in preferences in such situations, we split the data into 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 when an alternative is used alone and when it is used at

the same time as the opposite alternative. As we in this study are 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 a CV journey, both observations are taken out and vice versa).

The model was estimated using Python Biogeme (Bierlaire & Fretschler 2009) with 1000 MLHS draws. The results of the model estimation are reported in Table 4. All parameters have a plausible sign and most are significant. We also included parameters that were not significant at the 95% level to show that these effects have been tested as well. For total journey time, net driving time and number of trip legs, we did not find any difference in parameters between the alternatives. As expected, these all have negative signs.

As discussed earlier, EV trial participants often use the early trial period to present the EV to friends and neighbours. In the first week of the trial there is a higher parameter for the EV alternative compared to the rest of the trial, which could be due to a higher enthusiasm for using the EV but also due to presentation trips of the EV. Furthermore, we tested if there is a difference in parameter during the morning peak, where most car users are going to work and found a positive parameter for EVs. Home-work trips are easy to plan and a lower level of flexibility is often needed, which means that the EV is very suitable for this. The parameter for the first week interacted with the number of trip legs in each journey for EVs is positive and almost cancels out the negative parameter for the number of trip legs. We furthermore tested whether the number of necessary charges has an effect on the choice and found that taking the log to the number of charges explained the choice better. This makes sense as it is expected that the first necessary charge has a higher marginal disutility than the following charges.

**Table 4: Estimation of the mixed logit (ML) model for the choice between a CV and an EV for home-based journeys**

Name	Value	Robust t-value	p-value
Alternative Specific Constant, EV	4.5	9.46	0.00
Standard deviation of Alternative Specific Constant, EV	1.29	8.4	0.00
Total journeytime	-0.063	-1.86	0.06
Net drivetime	-0.069	-3.19	0.00
Number of trip legs	-0.781	-3.9	0.00
Number of driving licences, EV	-0.416	-2.51	0.01
Journey distance, km, EV	-0.003	-0.67	0.50
Number of EV charges necessary (log), EV	-1.6	-3.63	0.00
City dummy, EV	0.468	1.6	0.11
Battery level at journey start < 25% * journey distance, EV	-0.124	-3.54	0.00
Windspeed, m/s, EV	-0.39	-11.83	0.00
Precipitation, EV	0.514	2.23	0.03
First week dummy, EV	1.77	4.27	0.00
First week * Number of triplegs, EV	0.523	1.96	0.05
First week * Precipitation, EV	-0.582	-2.39	0.02
First week * Windspeed, EV	-0.264	-4.26	0.00
First week * Journey time, EV	-0.125	-3.78	0.00
Departure is between 7-9am at weekdays, EV	0.513	4.1	0.00
Number of observations:	4295		
Number of estimated parameters:	18		
Number of MLHS draws	1000		
Final log-likelihood	-1571.8		
Rho bar wrt. 0	0.466		

Including information about the weather highly improved the model. 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 CVs was only 20%. Similar results for EV efficiency are found in Zahabi et al. (2014) and Fetene et al. (2017). Inevitably, such a drop in efficiency will have a great effect on the driving distance provided by a fully charged battery which again should have an effect on the EV travel behaviour. Hence, we expected that a lower temperature would have a negative effect on the EV alternative. We tested several specifications for temperature, but surprisingly we were not able to find a strong effect of temperature on the choice. Instead, wind speed seems to explain the choice behaviour much better. Furthermore, precipitation has a positive and significant parameter. It appears that individuals chose the EV alternative more when it was raining. We believe that this result represents a weakness of the data, as we do not have information about the full choice set of the household transport options. Thus, when it is raining, it is possible that bike trips are replaced by the EV given that the household had access to this as an extra car during the trial period.

## 4. Discussion

In this section, we discuss the modelling results to see how they align with the assumption that CV and EV use in mixed car households are the same. Along with this discussion, we also address the various limitations set by the experimental design and the data.

Even though the participants were told to use the EV as the primary car, the results show that they still used the CV for a large share of their daily transport. This indicates that the type of EVs used in this trial cannot fulfil the requirements of a typical household. This could both practical limitations (e.g. insufficient driving range, booth size etc.) and psychological barriers for specific type of journeys. The literature has focused greatly on driving range and has in general found great discrepancy between several types of indicators of sufficient driving range based on current travel behaviour and the preferences for driving range (see e.g. a thorough discussion on the driving range paradox in Franke & Krems, 2013). Based on our results, we discuss this issue further. As mentioned earlier our modelling results capture both causal and spurious effects. We therefore discuss the results that we see as capturing causal effects below.

The DDT model shows that for both CVs and EVs, across all periods, population density in the area of the household leads to lower DDT. This effect captures that car use is lower in urbanised areas of Denmark due to shorter travel distances and better public transport. The modelling results also show some interesting differences as households located in city areas drive their CV significantly less. A similar effect was not found for EVs.

Furthermore, the DDT model shows that during weekends, the EVs are driven less and the CVs are driven more compared to weekdays. One explanation for this is that weekend journeys have more variation from short shopping trips to longer trips for visiting family, and less planned and thus require more flexibility. This assumption is also supported by the choice model, where we found a higher preference for EVs when a journey begins on weekdays in the morning peak, where journeys are mostly well-planned home-work journeys. As a journey becomes more complicated with longer journey time, more trip legs and more necessary charges, the probability of choosing the EV decreases. Currently, a potential EV household would therefore be a multi-car household (as also shown in Klöckner et al., 2013) so that the spontaneous or complicated trips can be covered with another vehicle or a household with a limited or well-planned car transport need.

Finally, the models show that weather affects EV use. Our DDT model show that when the temperature is low or when there is much wind, then it has a significant negative effect on DDT for the EV alternative. Wind speed also has a negative effect on the probability that the household chooses the EV instead of the CV for home-based journeys, but the effect seems to relax for users with EV experience. Thus, individuals seem to avoid the EV when it is windy and this effect is even stronger in the first week of the trial. This could be due to the high deviation in actual driving range dependent on several variables such as driving style and weather (Zahabi et al. 2014; Fetene et al. 2017). In many instances, e.g. if the weather is cold or if a journey is following a high-speed road, the driving range is usually much lower than the factory specifications of the car. Such variations create uncertainty, which in many cases will mean that other options are considered instead.

## 4.1 Limitations of the sample

We believe that our data analysis and modelling can be used to reject the hypothesis that CV and EV use will be the same given the technological differences. But we would like to acknowledge the limitations of our data given that the experiment was designed for other analyses than the one we present in the paper.

First, we can only look at the constraint situation where a household has one CV and one EV. However, we can see that the trip patterns for the EVs are similar to those of the CVs before the trial (Figure 1). This means that we are not studying the replacement of a CV with an EV but the specialised use of both alternatives in two-car households.

Second, the EVs available for the sample belong to the first generation of mass-produced EVs, i.e. the EVs available in the trial were mini class cars. In the years after the initiation of the project, several new EV models have been marketed offering more space, better driving performance, and the possibility of driving slightly longer on a fully charged battery. It would be interesting for future work to test whether the effects would be the same if the EV had been the same car class as the CV in the household.

Third, for a full picture regarding the choice between the vehicles, data on other transport modes should also be available. The data available for this study covers most of Denmark and in some areas there is a quite high share of public transport and bike travel (e.g. about 1/3 each for the Copenhagen municipality). Unfortunately, we only have data on the car alternatives and acknowledge that this can affect some of the parameters. For example, we find that the households a significant parameter for EVs when it is raining, which could be a result of individuals choosing the EV instead of bike when it is raining.

## 5. Conclusion

Existing literature on EV behaviour suffers from a lack of good information from actual EV users. Many EV studies rely on data from CV behaviour but these implicitly assume that users do not change behaviour when they use an EV instead of a CV. Other EV studies rely on self-reporting from actual users or participants in demonstration projects but such reporting can differ from actual behaviour. This study utilises a unique dataset with actual EV GPS data to study how the current technology differences might affect households' vehicle use. The data was collected in a large demonstration project, including detailed GPS data from both the EV and the CV in households that had access to both vehicle types over a long period of time. Due to the long period of the demonstration project, the members of the participating households were allowed to get used to having the car and optimise their daily mobility, including the option of using the EV, and it is *these* types of preferences we seek to investigate here. Furthermore, evidence from Norway (Klößner et al. 2013) shows that most EV households in Norway also have access to a CV. Thus, assuming this will also be the case in Denmark which is geographically close and culturally similar, most future EV households will have the choice between a CV and an EV at least for a horizon of 5-15 years. Therefore, we believe that the sample used for the analyses in this study is very relevant for studying the potential use of EVs in general. Even though the interest in EVs is rapidly increasing these years, it will probably still be some time before it is possible to explore EV mobility patterns from real EV users.

We have presented two different models that can be used to quantify relevant variables that affect EV travel behaviour. The main objective was to investigate if the current technological differences between EVs and CVs affect the daily household travel when such cars are available in a household. For the analyses, several variables describing the individual, the household, the weather and the geography were available. As far as we are aware, this study represents the first attempt to model how specific factors affect different indicators of EV usage in private households with access to both vehicle types.

The results of a mixed non-linear regression model for daily distances driven show that EV use was reduced during weekends whereas CV use increased on weekends in the final period of the trial. Furthermore, the results show that only EV use is reduced at lower temperatures and higher wind speeds. The results of a mixed logit model for the choice between the CV and the EV for a home-based journey show that the EV is mostly used for shorter trips during morning peaks on weekdays with less need for out-of-home charging. Thus, results from both models indicate that the EV alternative is preferably used for well-planned transport in comfortable weather conditions.

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