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Are electric vehicles better suited for multi-car households?

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Abstract

Electric vehicles could reduce CO2 emissions from the transport sector but their limited electric driving range diminishes their utility to users. Two-car households could be better suited for EV adoption since one vehicle could be used for longer trips. However, the number of days requiring adaptation and the differences between the cars in a multi-car household have not been systematically analysed yet. Here, we estimate the probability of daily driving above a fixed threshold for Swedish and German car driving data. We find the vehicles from multi-car-households to require less adaptation and be better suited for EV adoption which we confirm with an economic analysis.

Keywords: BEV, mobility, market

1 Introduction

Electric vehicles (EVs) could reduce global and local emissions from the transport sector [1]. Yet, the limited electric driving range of battery electric vehicles is technically and mentally a major hurdle for many consumers and impacts the EVs utility. The variation in distances travelled by one individual on different days of the year is important for the utility of EVs [2], [3]. In total, the limited range and long recharging times seem to impede EV adoption. On the other hand, EVs can easily be charged at home for most car owners, potentially yielding more comfort since extra visits to gas stations become unnecessary [4].

Multi-car households could be potential early adopters given the fact that there is always a long range vehicle available. In Norway, the country with the highest EV share per capita, 91% of the EV owners also have another car [5]. Furthermore, multi-car households have higher income [6], [7] and are thus more likely to afford the higher purchase price of EVs. On the other hand, higher income is correlated to higher annual mileage and could imply more trips that exceed the electric driving range of an EV. These trips would either have to be replaced by a conventional vehicle in the household or by renting another vehicle. In both cases the economic viability of the EV is reduced. Thus, multi-car households could be better suited for EV adoption but a systematic understanding of their driving behaviour with respect to the limited range of EVs and their role in market evolution does not yet exist. The line of argumentation for EVs in multi-car households builds on two assumptions. First, that the second car is commonly used for shorter, everyday trips compared to the first car or the car in a one-car household. Second, households may be able to shift between the cars to come around the range limitations of the EV. In this paper

we focus on the first part and address the following two questions: .Are the second cars in a multi-car household better suited as BEVs from a driving pattern point of view? And taking into consideration total costs, are these BEVs economical?
We study driving data from single-car and multi-car households in Sweden and Germany and analyse their individual distributions of annual and daily vehicle kilometres travelled (VKT). This analysis is used to calculate the number of days that have a driving distance that is larger than the electric range, days requiring adaptation (DRA), and to calculate the total costs of ownership while taking into consideration the extra costs of having to replace the BEV with another car.

Several studies have analysed the potential first user groups to adopt EVs. It is often stated that EVs are most likely to be used in large cities [8], due to their limited range and small size. However, [9] as well as [10] analyse car owner groups in Germany from an economic point of view and find that early adopters of EVs are likely to be those with a full-time job living in towns and cities with less than 100,000 inhabitants. For the UK, [11] focused on demographic and attitudinal variables in the adoption likelihood of EVs and concluded that BEVs are considered as possible second household cars by car buyers, whereas PHEVs are also taken into account as the main or only vehicle. Low range anxiety and an EV friendly social environment are found to be strong factors in favour of EV adoption. An online survey in the US found that early adopters of EVs are young or middle-aged and have a bachelor degree or higher [12]. They did not find any evidence that household income influences the likelihood of EV adoption, unlike [13]. The role of the availability of more than one car in the households seems to be disputed. [4] find that it increases the probability of adoption while [12] conclude that it does not affect the willingness to buy an EV. The same authors also conclude that economic motives such as fuel cost savings are more decisive for EV adoption than reducing CO2 emissions. The findings of a survey by [14] indicate that costs and range are rated most important for adoption, while reducing petroleum use was seen as the major advantage. The fact that costs are important is not that surprising given that it is often one of the determining factors for vehicle choice (see e.g., [15]–[18]). A UC Davis study [19] finds that range anxiety was not that much of a problem during a longer trial period. However, it should be noted that these households all had an additional conventional vehicle. So did the trial households in [20] where they found that some trips were shifted between the vehicles in the household, however there was still a demand for a longer range.

Overall, the findings concerning the early adopters of EVs are still not conclusive and most of the studies focus on the US. Apart from attitudinal factors, the studies suggest that early buyers are likely to have a higher-than-average income [21]. For the present study, with its focus on multi-car households, range anxiety is a relevant finding of the studies cited-above since a multi-car household has at least one back-up vehicle (which we assume to be a conventional vehicle due to the currently low market diffusion of EVs). Thus, we take a user perspective and analyse the technical and economical suitability of EVs in single- and multi-car households. Surprisingly, the importance of a second household car has not received much attention in the literature. The present study thus differs from previous work by explicitly comparing single- and multi-car household with respect to their suitability for EV adoption. Furthermore, it is – at least to our knowledge – the first study analysing the Swedish and German market in this respect.
The outline of the paper is as follows. In section 2, the methodology used, the technical and economic assumptions as well as the driving data are described. Section 3 contains the results and is followed by a discussion in section 4. We close with a summary in section 5.

2 Data and Methods

2.1 German and Swedish driving data

We use two data sets to analyse the differences between single-car and two-car households. The data sets comprise vehicle motion data from Germany [22] and Sweden and the average observation periods range from 7 days for the German data to 58 days for the Swedish drivers. The different data sets are summarised in Table 1.

Table 1: Summary of data sets.

Name of data set	Mobility Panel	SCMD
Location	Germany	Sweden
Collection Method	Questionnaire	GPS

Sample Size	6,339	429
Avg. observation period	7 days	58 days

The German Mobility Panel [22] is an annual household travel survey which was initiated in 1994 and is available to the authors until 2010.

Since MOP is a household travel survey which focuses on people and their trips, we have to assign trips to vehicles if unambiguously possible (see [23], [24] for details). By using all data from 1994 until 2010, we obtain 6,339 vehicle driving profiles with 172,978 trips in total. Besides the driving, the profiles contain socio-economic information of the driver (e. g. age, sex, occupation, household income, education) and the vehicle (e. g. vehicle size, vehicle owner, garage availability).

The Swedish Car Movement Data (SCMD) consists of GPS measurements of 429 privately driven cars in western Sweden. Measurements were evenly distributed over the years 2010-2012. The cars were randomly sampled from the Swedish vehicle registry with an age restriction on the car of maximum 8 years. Western Sweden is representative for Sweden in general in terms of urban and rural areas, city sizes and population density. The sample is representative in terms of car size and car fuel type. In relation to the household of the cars there is a slight overrepresentation of cars being a first car in a household compared to the national average, this is due to the age inclusion criteria in the sampling. Similarly the cars in the data have a higher annual VKT of 17154 km compared to about 13,000 km for the national average, this is also due to the younger age of the cars compared to the national average. With regards to the age of the drivers, there is a slight over-representation of senior citizens. A full description of the data including pre-processing is available in [25].

The SCMD data distinguish between cars belonging to single car households as well as first and second cars in multi-car households based on the annual VKT. Thus first cars on average have a higher annual VKT compared to second cars, which has implications for both the DRA analysis and the economic analysis.

Table 2 contains an overview of the summary statistics of both data sets. Note that average daily VKT are the user-specific averages and range from 0.29 km per day to up to 469 km per day for the one week data from Germany.

Table 2: Summary statistics of driving behaviour.

	Min	0.25	Median	Mean	0.75	Max
SCMD data (N = 429)						
Observation period [days]	30	51	59	58	64	147
Share of driving days	0.21	0.67	0.83	0.8	0.96	1
Daily VKT [km]	6.9	38.4	51.9	57.1	72.3	172.0
Annual VKT [km]	1,715	9,570	14,933	17,154	21,903	71,347
Mobility panel data (N = 6339)						
Observation period [days]	Seven for all drivers by design					
Share of driving days	1/7	6/7	7	0.92	7	7
Daily VKT [km]	0.29	22	28.3	50.6	65	469
Annual VKT [km]	15	8,000	12,000	13,830	17,000	260,000

2.2 Methods

In the innovation adoption literature, both the adopter characteristics and the characteristics of the innovation have been found to be important predictors of innovation adoption [26], [27]. Here, we focus on the innovation itself, i.e. the EV, and try to estimate for which potential users an EV is more suitable – single- or multi-car households. We focus on a technical and economical evaluation. These characteristics are easily measurable and likely to play an important role in the purchase decision for EVs [10], [12]. Furthermore, we analyse suitability on an individual user level instead of discussing average values and average driving patterns. This is particularly important for EVs in the presently early market phase when this new technology is not economical for all users but only in certain niches. To identify these niches, a large data base of individual users with their wide range of vehicle usage and economics is studied.

It should be clearly noted that we do not do any optimization of car selection for different trips within a household (since neither of the data sets have data on both cars in a two-car household). This limits the study in the sense that a two-car household may be able to do more short trips with their BEV and more (or possibly all) of the longer trips with the alternative car. Methodologically, our analysis uses standard methods of technology assessment (as in [28]) including scenarios and model-based assessment. Similarly, our results are no forecast of exact future market shares but are an assessment of potential user groups for this new propulsion technology.

2.2.1 Estimating the number of days requiring adaptation in the German data

An understanding of the distribution of daily VKT allows us to estimate the probability of rare long-distance travel [29]. Here and in the following, we only consider daily VKT instead of the length of individual trips.

The individual daily VKT r_l are assumed to be independent and identically distributed (iid) random variables. Let $f(r)$ denote the user-specific distribution of daily VKT. The probability of driving more than L km on a driving day is then given by $\int_L^\infty f(r)\mathrm{d}r = 1 - F(L)$ where $F(r)$ is the cumulative distribution function of $f(r)$. Let n denote the number of driving days out of N days of observation such that $\alpha = n/N$ is the share of driving days. Thus, $D(L) = 365(n/N)[1 - F(r)]$ is the number of days per year with more than L km of daily VKT. Accordingly, $D(L)$ is the number of days requiring adaptation for a potential BEV user. Following [29], we use the log-normal distribution $f(r) = \exp[-(\ln r - \mu)^2/(2\sigma^2)]/(r\sqrt{2\pi}\sigma)$ to model the random variation in daily VKT of the drivers. For each individual driver, the log-normal parameters for the typical scale of daily driving μ and the variation in daily VKT σ are obtained by maximum likelihood estimates.

The number of days requiring adaptation is calculated as follows. For each driver the share of driving days is estimated as n/N and the driver-specific log-normal parameters are estimated from likelihood maximisation. Using the cumulative distribution function of the log-normal distribution $F(x) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{\ln x - \mu}{\sqrt{2}\sigma}\right)\right]$ the user-specific number of days requiring adaptation $D_i(L)$ is calculated. This procedure is repeated for each driver in the data base. In very rare cases (37 out of 6339), there is no variation in daily driving distance between the days reported, i.e., $\sigma_i = 0$. We set σ_i equal to the sample mean in this case. However, this has almost no effect on the results reported below. Please note that this log-normal estimate is expected to be valid for different driving ranges L but seems to slightly overestimate the actual number of days requiring adaptation [29].

2.2.2 Estimating the number of days requiring adaptation in the Swedish data

In the Swedish data we similarly aggregate the GPS measured trips into daily driving distances. The number of days requiring adaptation (DRA) for the different users is then counted and linearly scaled up to a yearly basis. Similarly the annual VKT is scaled up from the total driving during the measurement period.

2.2.3 Analysing the economics of potential BEVs

We want to compare the economics of BEVs in single- and multi-car-households. Thus, we only calculate the TCO as

$$TCO_a = a^{capex} + a^{opex}$$

which consist of annual capital (a^{capex}) and annual operating expenditure (a^{opex}) for pure battery electric vehicles (BEV) and – as reference cases – two conventional vehicles (powered with gasoline and diesel).

For the capital expenditure, we use the discounted cash-flow method and calculate the investment annuity for user i as

$$a_i^{capex} = p \cdot \frac{LP_i \cdot (1+p)^{T_1} - SP_i}{(1+p)^{T_1} - 1}$$

where p stands for the interest rate, LP_i for the net list price for vehicle i and SP_i for its resale price, while T_1 is the vehicle investment horizon for the first vehicle purchase.

The operating expenditure (a^{opex}) for user i is calculated as:

$$a_i^{opex} = VKT_i \cdot \left(c_{e/c} \cdot k_{e/c} + k_{OM}\right) + k_{tax} + k_{rent_i} \cdot D_i$$

It comprises driving dependent and driving independent costs. The cost for driving consists of the specific consumption for electric or conventional driving ($c_{e/c}$) in kWh/km or l/km and the specific cost for electricity or fuel ($k_{e/c}$) in EUR/kWh or EUR/l. By adding the cost for operations and maintenance (k_{OM}) we obtain the specific costs per kilometre which are multiplied by the annual vehicle kilometres travelled (VKT_i) for the driving dependent cost.

Driving independent costs consist of annual vehicle tax (k_{tax}) and the cost for a rental car (k_{CI_i}) multiplied by the number of days that exceed the driving range of a BEV (D_i) deriving from the first part of this analysis. For more details on this, see [24], [30].

In the economic analysis we distinguish between economic BEVs, uneconomic BEVs, and non-BEVs. A car is considered a BEV if it has a number of DRA below a certain limit (such as maximum 12 DRAs per year), then it can be either an economic or uneconomic BEV according to the economic analysis. All cars with more DRAs than the limit are counted as non-BEVs.

2.3 Technical and economic assumptions

While the estimation of the number of trips for which battery electric vehicles are not suited is mainly based on the driving profiles (sec. 2.1) and the assumption that log-normal is the best fit for this analysis, we need several technical and economic assumptions for the economic analysis.

Firstly the technical assumptions comprise battery sizes, depths of discharge of the batteries as well as the electric and conventional consumptions. With the first three we are able to calculate the electric driving ranges (L) of the vehicles. Since current prices and economic framework conditions are still disadvantageous for EVs, we use a scenario with economic and technical parameters for the near future (which could be around 2020). The analysis could also have been performed for present day values, yet some of the parameters, in particular battery prices, are quickly changing at the moment and more likely to remain at stable values in the near future. Furthermore, near future framework conditions allow to analyse a higher number of economical driving profiles, making the results below more robust. All technical parameters are given in Table 3 and the economic parameters in Table 4 and 5.

Table 3: Technical assumptions for the analysis (all values for 2020)

Attribute	Battery capacity	Depth of discharge	Electric consumption	Electric range	Conventional consumption (gasoline)	Conventional consumption (diesel)
Unit	kWh	-	kWh/km	km	l/km	l/km
Parameter	24	95 %	0.211	120	0.065	0.053
Reference	[31]	[31]	[32]	Calculated	[32]	[32]

Secondly we make certain assumptions for the cost of vehicles. All cost parameters are given with VAT and are made for 2020 in Table 4. They are different for Swedish and for German vehicles. Generally, the parameters are more favorable for Sweden with a higher gasoline and diesel price, a lower electricity price and a direct subsidy for environmental cars to vehicle consumers upon purchase. Thirdly we need several assumptions for some framework conditions such as electricity price, fuel prices, investment horizons and interest rates. All these can be found in Table 5.

Table 4: Vehicle cost assumptions for the analysis (all values for 2020 incl. VAT)

Attribute	Unit	Sweden	Ref.	Germany	Ref.
BEV price w/o battery	EUR	23000	[33]	21,500	[33]
Diesel vehicle price	EUR	24630	[33]	23,400	[33]
Gasoline vehicle price	EUR	21900	[33]	20,800	[33]
O&M BEV	EUR/km	0,05	[34]	0.040	[34]
O&M Diesel	EUR/km	0,06	[34]	0.048	[34]
O&M Gasoline	EUR/km	0,06	[34]	0.048	[34]
Vehicle tax BEV	EUR/yr	0	[35]	0	[35]
Vehicle tax Diesel	EUR/yr	209	[35]	209	[35]
Vehicle tax Gasoline	EUR/yr	101	[35]	101	[35]
Rental car cost	EUR/day	60	[36]	60	[36]
BEV subsidy	EUR	4400	[37]	-	

Table 5: Framework conditions [all prices incl. VAT]

Attribute	Unit	Sweden	Ref.	Germany	Ref.
Electricity price	€/kWh	0,175	[38]	0.29	[39]
Gasoline price	€/l	2,06	[40]*	1.65	[34]
Diesel price	€/l	2,10	[40]*	1.58	[34]
Battery price	€/kWh	416	[38]	335	[33]
Investment horizon	years	8		6.2	[33]
Interest rate	-	5%		5%	[33]
VAT	-	25%	-	19%	-

*Original numbers from 2011 and linearly scaled up to 2020 with the expected increase in prices from [34]

3 Results

3.1 How often are long-distance trips performed by first and second cars in households?

We analyse both data sets with respect to the share of vehicles with a certain number of days requiring adaptation with a battery electric vehicle for single and multi-car households. The results for a battery range of 120 km are shown in figure 1 and 2. For the Swedish data, the results are extrapolated directly, while for the German data we have estimated the best-fitting log-normal distribution (see Methods section).

For the German case, the data set has been limited to vehicles including information on the number of vehicles in the household and only households with one or two vehicles were studied. If the household has two vehicles at its disposal, the reporting household decides which vehicle's trips they reported first. Since the distinction between first and second car is somewhat arbitrary in the German data, the household's decision about the first vehicle to report has been used as proxy for 'first car'. The other household car, reported as second instance, has been identified as 'second car'. For each vehicle, the seven days of observation have been used to find the vehicle-specific best fitting log-normal distribution (by maximum likelihood estimates). The resulting μ and σ are both individually normal distributed (the mean of the μ is 3.3 with a standard deviation 0.7, the mean of the σ is 0.9 with a standard deviation of 0.4). Following the method described in section 2.2.1, the individual number of days requiring adaptation has been calculated for each vehicle. In total, there 6,339 vehicles in the German data including 4173 vehicles from single-car households, 956 vehicles are first cars in two car households, 951 vehicles are second cars in two-car households. The remaining 259 vehicles are from households with more than two cars and have not been analysed here.

Figure 1 shows the empirical cumulative distribution function of the share of vehicles with less than a certain number of DRA annually in the Swedish data for a range of 120 km. The cars are separated into their respective household categories. We find the distribution of DRA from single car households to be similar to that of all cars.

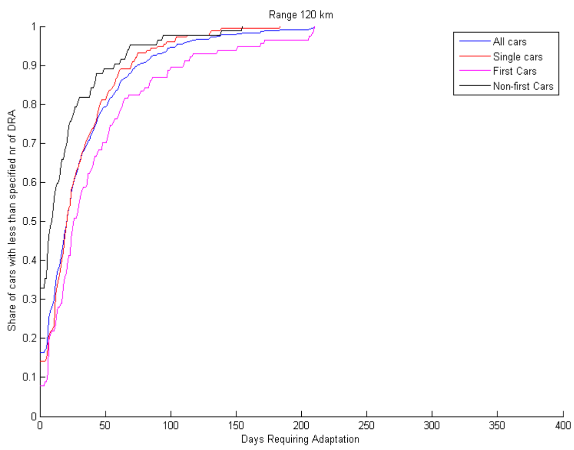

Figure 1: CDF of days with driving of more than 120 km in the Swedish data.

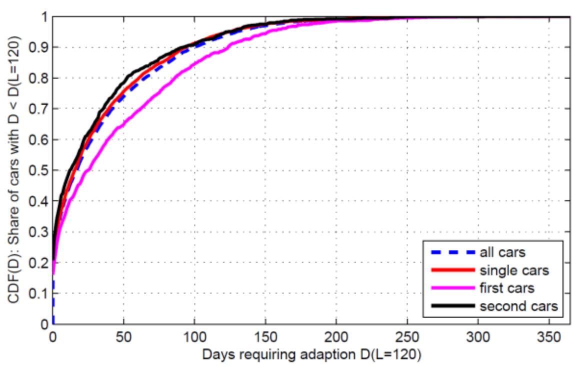

Figure 2: CDF of days with driving of more than 120 km in the German data.

Figure 2 shows the same CDF for the German data, here the CDF is estimated from the best-fitting log-normal distribution for each vehicle. The distribution of days requiring adaptation is similar for single-car households and the second car in a two-car household. The first car in a two-car household, however, is more likely to require adaptation since a higher share of users drives more than 120 km daily VKT on a fixed number of days. For example, only 25 % of the single-car household vehicles drive more than 120 km on more than 50 days per year compared to 35 % of the first cars in two-car households.

In both data sets we find that at least 30% of the second cars in multi-car households have no days requiring adaptation. For the Swedish data, this can be compared with about 8% for the first car in multi-car households or about 15% for cars in single car households. For the majority of the cars in the Swedish dataset a second car typically has half, or less than half, of the number of days requiring adaptation compared to a single car, and even less in relation to a first car. For the German dataset the results are similar. This confirms that multi-car households are better suited for adopting EVs, though it should be remembered that, without a change in driving patterns, the second vehicle still has a number of days requiring adaptation.

To understand what causes some second cars to perform better than others we have analysed the Swedish data for the number of days requiring adaptation for different annual VKT. The results are shown in figure 3. Again the vehicles are separated on single car households, first cars, and, second cars in multi-car households and displayed as triplets of bars w.r.t. annual VKT. As expected there are fewer first cars with a low annual VKT, and fewer second cars with a high annual VKT. The number of days requiring adaptation grows with the annual VKT as expected. It can be noted that for annual VKT up to 10,000 km, more than half of the second cars have no days requiring adaptation, while for first cars, there is a much smaller fraction requiring no adaptation. This hints at second cars have more regular daily driving distances compared to first cars, and thus, are more suited to be replaced by battery EVs. For annual VKT above 30,000 km, there are no cars with less than one day per week requiring adaptation. Thus, annual VKT is important for the probability that a car is easily replaced by a battery EV.

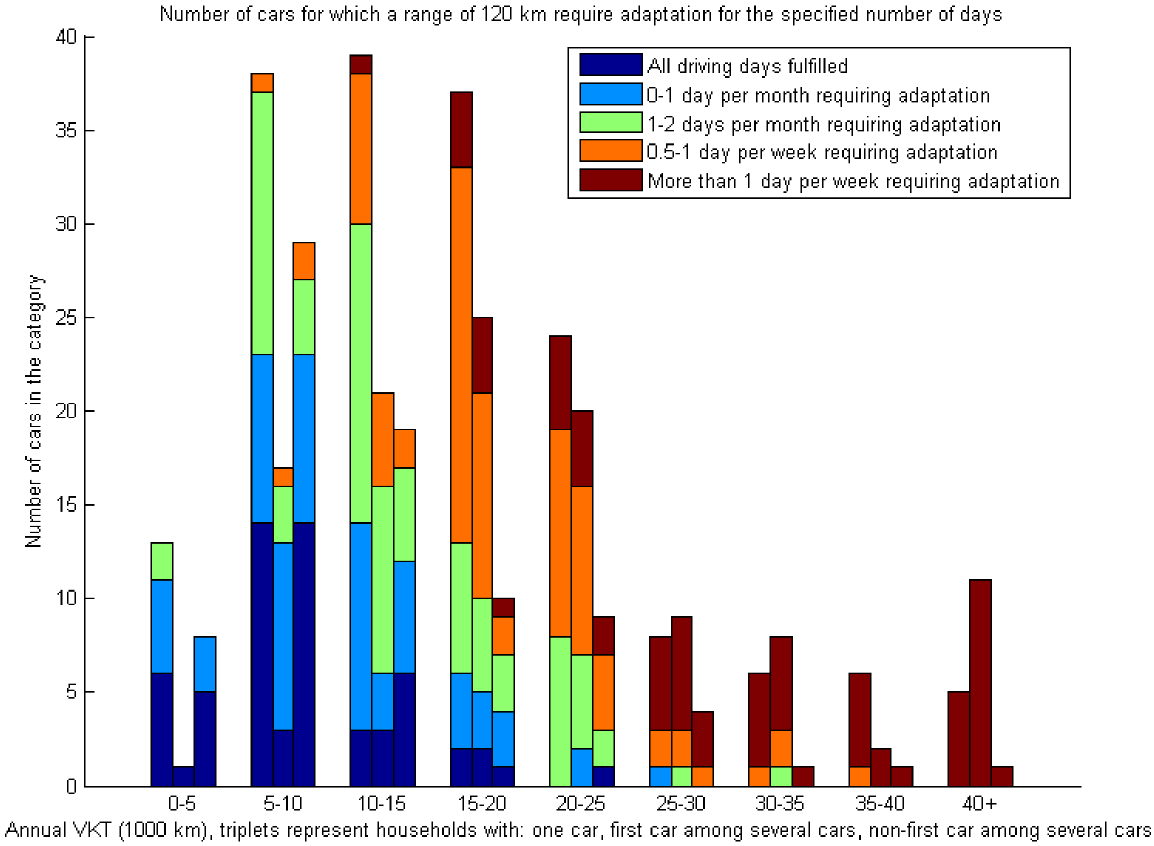

Figure 3: Number of cars for which a range of 120 km require adaptation for the specified number of days

3.2 Can BEVs economize as second cars in the households?

The results for the economic analysis for Germany can be found in Figure 4. We show the total number of driving profiles with a DRA limit of 52 days (once per week) with circles using the left y-axis and distinguish by cars in single car households, first and non-first cars in multi-car-households. On the right y-axis, we find the market shares of BEVs distinguished in the same manner. Within this part of the analysis a multi-car-household is defined when it was stated in the questionnaire that the household contains more than one vehicle. This is different to the definition in section 3.1 where we defined a multi-car-household when more than two vehicles were driving. As not all vehicles of each household were reported, we cannot tell if all the “first cars” are included in the analysis.

Observing the number of vehicles in the households in figure 4, we find that the number of single car households is always higher than the number of first or non-first cars in multi-car-households and that the difference decreases with increasing VKT. This is mainly a result from a higher number of single cars in the data. First cars in multi-car-households seem to drive slightly more per year than other cars, although this is an unsteady interpretation keeping the difficulty to distinguish between first and other cars in mind. The shares of economic BEVs increase with increasing VKT since BEVs then are able to economize due to lower running cost. Although the shares rise up to 100% the total number of vehicles is low (52 out of 6339 vehicles are economic BEVs for the German data set). Nonetheless, the share of vehicles in multi-car-households is always higher than in single-car-households while the numbers of vehicles within these VKT-classes are almost equal to each other. This gives a first hint that BEVs might be better suited for multi-car-households in Germany, though we cannot make a distinction between first and second cars in this case.

Figure 5 uses a similar display for the Swedish data and shows the number of economic and uneconomic BEVs for a DRA limit of 12 days and a battery range of 120 km. We use 12 instead of 52 days, since increasing the DRA would not lead to more economic BEVs, since the cost for DRAs lets BEVs become less economic compared to conventional fuel vehicles. As can be seen, a low annual VKT yields more BEVs because of the fewer DRAs that follow a low driving distance, but a higher annual VKT is needed to make these cars economical. The result is that a plateau of most economic BEVs occurs at annual VKTs from 10,000 to 20,000 km. This range is lower than for Germany which results from different assumptions for costs. A slightly higher share of second cars turn out as economical BEVs compared to first cars or single cars, but the difference between the household categories is not as pronounced as when we only measure DRAs (figure 3).

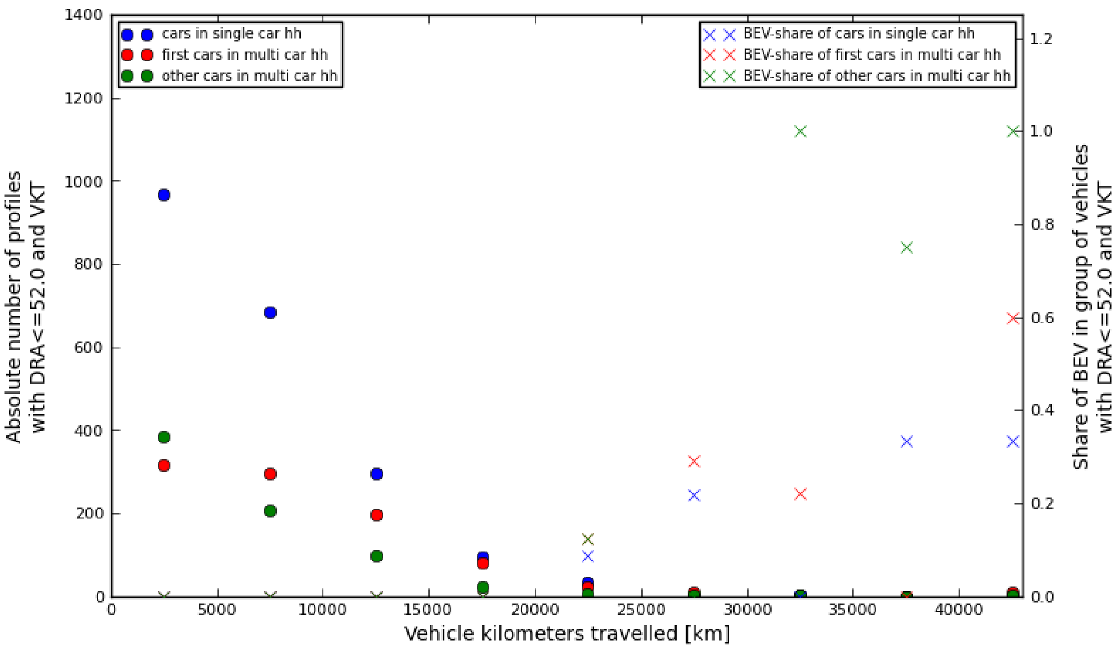

Figure 4: Total number of profiles (circles, left y-axis) and share of economic BEV (crosses, right y-axis) distinguished by household category w.r.t. annual vehicle km travelled for German data. Range 120 km, accepting 52 DRA per year.

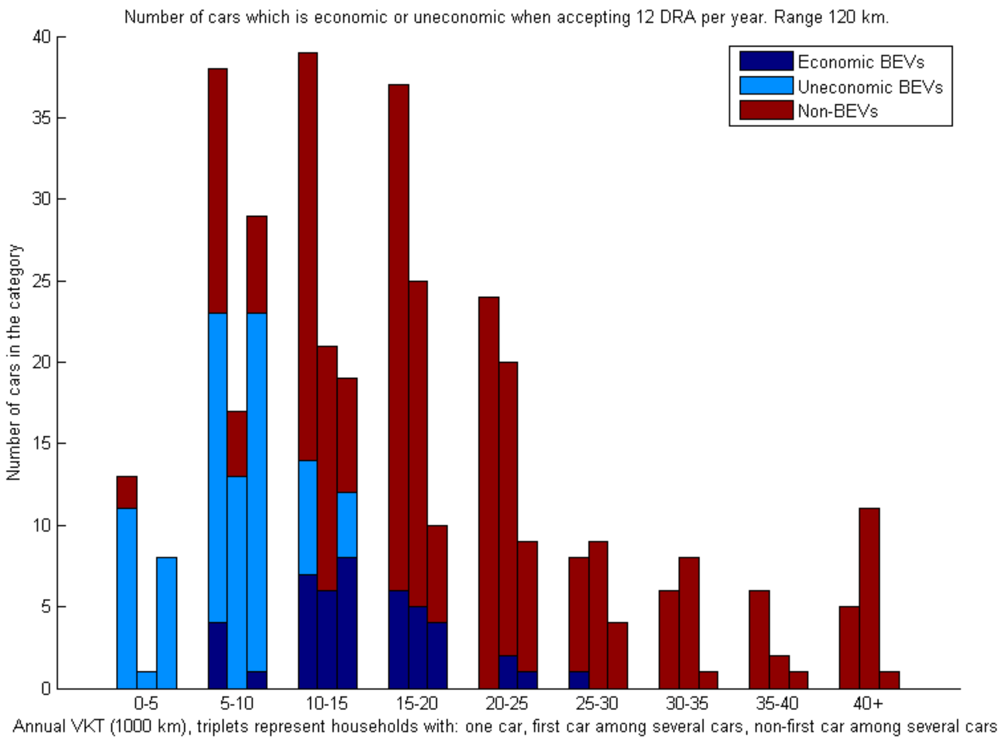

Figure 5: Number of economic BEVs, uneconomic BEVs, and Non-BEVs w.r.t. annual vehicle km travelled. Range 120 km, accepting 12 DRA per year.

Figure 6 shows more directly how the different household categories perform relative to each other with market shares of BEVs within their household categories with respect to DRA for Sweden on the left and Germany on the right panel. For Sweden second cars perform best relative to the others when accepting fewer DRAs, this is an effect of second cars having more regular driving compared to first cars, with fewer really long driving days. Again, it should be noted that this effect holds true even when first and second cars have the same annual VKT. First cars outperform the other categories when many DRAs are accepted, this is because a higher DRA limit enables many more first car with a high annual VKT to come into play compared to second cars. It should also be noted that the derivative of the second car curve is smaller compared to the first cars, specifically the share of second cars that turn out as economic BEVs doubles when increasing the DRA limit, while for first cars it increases by a factor of six. This has two reasons: one is again the higher regularity for the driving of second cars, and the other is that more second cars have a low annual VKT compared to first cars.

For Germany the results are different: We find many more first cars in multi-car-households to be economic as BEVs (about 2.5 %) than in the two other household groups (~0.2 %). This is again subject to the unclear distinction of first and other cars in multi-car-households performed by the panel participants. However, this evidently shows that vehicles from multi-car-households are more interesting for BEVs than in single-car-households within the German data set.

To summarize, we find an increasing share of BEV users with rising VKT until the number of days requiring adaptation is too high for BEVs to economize. The difference in economic outcomes for BEVs in Sweden and Germany is mostly due to the strongly differing economic parameters. The different annual VKT (due to the age of the included cars analysed) plays a role, but not as strong one as the economic parameters. However, our economic analysis shows that BEVs are slightly better suited for multi-car-households in Sweden and much better in Germany.

A note can be made about the direct subsidy in Sweden, were we to remove this subsidy, we would still have some economical BEVs, but the total number would be about one fifth of what it is now.

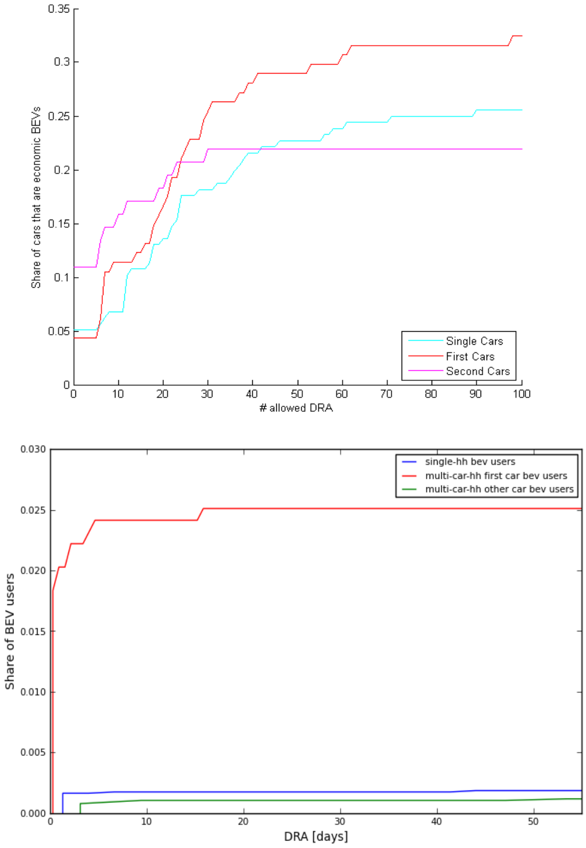

Figure 6: Comparison of share of economical BEVs w.r.t household and accepted DRAs. The shares are calculated as quotients of all cars in a specific household category. Swedish results above, German below.

4 Discussion

We assessed the suitability of EVs in single-car households as well as for the first and second car in multi-car households. We find that EVs are technically and economically better suited for multi-car households. However, our analysis relies on several assumptions that need to be addressed.

First, the distinction between first and second car is – to a certain extent – arbitrary, In the Swedish data set the first car is defined as the one that is driven the most, whereas in the German data set the first car is identified as the car first described by the survey participants. Despite this vagueness of the first-second car distinction, our results show clear differences between the technical suitability – as measured by the days per year requiring adaption – according to both definitions. This indicates robustness of our findings. Furthermore, the sole existence of a second car that could be used as back-up increases the suitability of vehicle with limited range in these households. Of course, the two vehicles could show a long-distance trip on the same days. However, further research is required to analyse the likelihood of such events.

We presume that the cars are only recharged at night; giving possibility for daytime charging, e.g. at the workplace, would imply more days for which all the driving requirement is fulfilled. This would also have consequences for the economic analysis since more driving on electricity would make more BEVs economically viable.

We find that annual VKT is an important factor when looking at the number of DRAs. As a vehicle ages the annual VKT decreases, it is thus likely that the vehicles with fewest DRAs are also the oldest vehicles. However, when an EV is purchased one will presume that it's new and would have a profile more similar to the new vehicles with longer VKTs and more DRAs. This is not taken into account in our analysis.

In our economic analysis we compare a conventional vehicle and an EV only based on costs and do not at all take into consideration the socio-economic characteristics of the owner. The willingness to pay for EVs in some groups might be higher than in others. This was, e.g., found in early adopters of hybrids in California [41]. Thus a targeting of potential early adopters may lead to higher adoption rates.

5 Summary and conclusions

The argument that BEVs are better suited for two-car households rests on two assumptions. One is that the second car of a household has fewer long driving days and more regular driving compared to the first car or to cars belonging to one-car households. The second argument is that the household may be able to optimize their driving in such a way so that the BEV takes the majority of short trips and the conventional car takes the majority, or all, of the long distance trips. In this paper we have analysed the validity of the first of these arguments with real world driving data from Sweden and Germany. We find that the second cars have slightly more regular driving patterns with fewer long distance driving days and thus are better suited to be replaced by a BEV compared to the first car. This is especially true for the car groups with a low annual VKT since these have few DRA. However, even within these groups there are many second cars that are not suited for replacement by a BEV from a daily driving distance perspective.

When restrictions on economic viability are implemented, the difference in performance between second, first and single cars are reduced further, though still, the second car fits the requirements of the BEV better than the others. In the German data it is not clear that it is specifically the second car that is better, rather cars in multi-car households in general.

There are differences in the results between the Swedish and German data, these differences are however most pronounced in the economic analysis and are thus caused mainly by the economic parameters rather than differences in driving behaviour. To fully answer the question of how much better a multi-car household is for adopting a BEV one needs to address the second argument above as well. To do this, one should analyse the driving patterns of both cars in a two-car household and see how they can be optimized in relation to the limited range of a battery electric vehicle.

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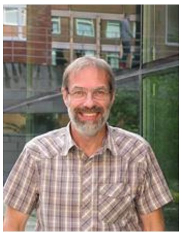

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