A Report on Energy consumption and Range of Battery Electric Vehicles Based on Real-World Driving Data

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Summary

Quantification of the energy consumption of Battery electric vehicles (henceforth, BEVs), and the factors affecting the energy consumption rate from real-world data, which is relevant to predict the driving range of BEVs, to investigate and recommend the cost saving driving patterns for BEVs is limited. This paper presents the energy consumption rate per unit distance driven and the range of BEVs under the Danish driving environments. The paper also investigates the factors affecting energy consumption rate per unit distance driven of BEVs. We used four data sources to accomplish the above mentioned objectives; driving pattern data collected from real-traffic 741 BEV drivers covering more than a quarter of a million trips and about 2.3 million km distance travelled that are extracted from GPS, drivers' characteristics obtained from registered data and two stated preference surveys conducted before and after the drivers experience driving BEVs, road characteristics data collected from GPS and map-matching and weather information extracted from the internet. We found that the mean energy consumption rate per kilometer distance driven of the BEV used in our data, namely, Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev, is about 181 watt-hour/km (about 45 % higher than the rate obtained from the car's specification), and the corresponding range is about 94 kilometers (about 27 % lower than the range obtained from the car's specification) if the BEV is to be driven until a fully charged battery is completely used. This implies that the real-driving range of these BEVs under the Danish driving environment is about 70 to 94 km since the drivers may not drive the cars until the battery is completely used; otherwise the battery may get flat on the way before the drivers arrive at a charging station to recharge the battery. We found that the main determinants of the energy consumption rate include driving patterns (acceleration and speed of driving) and weather variables. The driving range of BEVs is about 25 % less (76 km versus 103 km) and the energy consumption rate is about 62 watt hours higher in winter than in summer indicating that the current BEVs may not be suitable in countries with very hard and extended winter. We also found that the energy-saving driving speed is about 45 km/h to 54 km/h, and the temperature rate is about 14 ^{0}C, at least for the data we used. Moreover, we observed that the battery depletion rate per unit distance driven is not constant.

Contents

Table of Figures

1. Introduction

The transport sector being one of the largest contributor of greenhouse gas at global level (Zahabi et al., 2014; Alessandrini et al., 2012), there have been efforts to improve the fuel consumption of the sector by car making companies, which use improvement in fuel consumption as one means of competition, by many governments who use different policies that encourage fuel efficiency of vehicles, and by car drivers to reduce the average cost of driving. For example, the European Union and the US governments have set standards that limit the pollution level of cars and they use discriminatory fuel taxes to induce car manufacturers to produce, and car users to use fuel efficient vehicles (Kono et al., 2008). Battery Electric vehicles are considered as one alternative to curtail pollution from the sector and to reduce dependence on the scarce and insecure petroleum since the electricity needed to charge EVs can be obtained from renewable resources such as wind, solar power and hydro.

Analysis of the factors that affect the fuel consumption of vehicles is crucial to identify the main factors affecting fuel consumption of cars and to compare the relative performance of different cars under different driving environments. The fuel consumption of conventional cars is well-documented both in the theoretical literature (G. Mellios et al., 2011; Nam and Giannelli, 2005) and in the empirical literature (Brundell-Freij and Ericsson, 2005; Ericsson, 2001a; Hu et al., 2012). Hu et al. (2012) found that driving on wider streets is better than narrow once in terms of pollution level by affecting driving patterns that also noted by Brundell-Freij and Ericsson (2005), Isakov et al. (2007) and Kono et al. (2008). Previous studies also found that road grade, (Nam and Giannelli, 2005; Wang et al., 2008), traffic volume (congestion level) of roads and speed limits (Brundell-Freij and Ericsson, 2005) have significant impact on energy consumption rate of conventional cars. Isakov et al. (2007) have found from 1.4 to 2 fold differences in fuel consumption and emission rate among light-duty gasoline vehicles in China due to differences in road structure. A bunch of studies found that driving patterns (such as speed and acceleration) are the main factors affecting fuel consumption and pollution level of conventional cars (El-Shawarby et al., 2005; Ericsson, 2001a; Heide and Mohazzabi, 2013; Nesamani and Subramanian, 2006; Wang et al., 2008). Fotouhi et al. (2014) and Kono et al. (2008) found that the use of traffic information plays a significant role in energy consumption rate of cars. A number of studies have provided mathematical and technical detailed accounts of the effects of different car characteristic on fuel consumption of conventional cars. See, for example, EPA (2014), Heide and Mohazzabi (2013), Nam and Giannelli (2005), and Brundell-Freij and Ericsson (2005). The effects of car features on fuel consumption are technical issues that are usually taken into account during the design of the car by the manufacturers, and are usually made available to the consumers during the purchase of the car (Ben-Chaim et al., 2013; Kono et al., 2008).

There are also studies about the fuel economy and its determinants for hybrid electric vehicles (henceforth, HEVs) that use both fuel and rechargeable battery. For example, Zahabi et al. (2014) found that the fuel efficiency of HEVs could decrease up to 20 % during winter, and the overall fuel economy of HEVs relative to conventional cars could be overweighed by the poor performance of HEVs in places where there is very low temperature and extended winter. See also studies by Lohse-Busch et al. (2013), Alvarez and Weilenmann (2012) and Fontaras et al. (2008) about the impacts of temperature and driving environments on the fuel consumption of HEVs. In their analytical and simulation study, Banjac et al. (2009) found that the topology of the HEV, the power ratio of its components and the applied control strategy have strong impact on energy consumption rate of HEVs.

Due to range anxiety of fully battery EVs (henceforth, BEVs) associated with limited range, long charging time and spatially limited charging infrastructures, studies about the energy consumption rate and the corresponding range of BEVs as well as about the factors that affect the energy consumption rate of BEVs from real-world data is crucial to find a reliable prediction of the range, to evaluate and compare the performance of BEVs relative to other cars, to investigate and to recommend the cost-saving driving patterns for BEVs.

However, such studies about BEVs are scarce mainly due to the recent market penetration of BEVs. Of course, there are few studies conducted by car manufacturers and other stakeholders, see, for example Duke et al. (2009), but there are usually large differences between real-world results and results obtained by car manufacturers (Huo et al., 2011) for several reasons. For example, manufactures usually test BEVs from a long and continue driving until a fully charged battery becomes flat (Seredynski P. and O'Dell J., 2013) in that the energy used to overcome the inertia force to propel a parked car and the energy used to cool down a propelling car for each real-world short trips is saved in manufacturer testing. There are also experimental studies (at lab) that tested the effect of some parameters on the range and energy consumption rate of BEVs. For example, Lohse-Busch et al. (2013) investigated the impact of ambient temperature on BEVs in comparison with other types of vehicles, and they found that BEVs are more sensitive to temperature, particularly to cold temperature. They observed 100 % increase in energy consumption rate for Leaf BEV when the temperature drops to 20 ^{0}F from 70 ^{0}F, while the increase in energy consumption rate for a conventional car was only 20 %.

A study about the energy consumption rate and the corresponding range of BEV as well as about the factors that affect energy consumption rate using real-world data that takes the drivers' characteristics, weather variations across years and over wider spatial area including urban and rural areas, and different road characteristics in to account is missing. The purpose of this paper is to fill this gap in general, and in particular, under the Danish driving environment by analyzing a real-world data collected over the period of three years.

Specifically, this paper presents the range, energy consumption rate and its determinants of BEVs under real-world driving patterns and environments in Denmark including weather condition, drivers' household characteristics, road characteristics and car features. The paper used data collected from real-traffic BEV drivers that consisted more than a quarter of a million registered trips covering about 2.3 million km distance. The trip data were collected by Clever, Electric mobility operator in Denmark, from 758 customers[1] who has been driving three models of BEVs, namely, Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev for about 3 to 6 months during the period from January 2012 to January 2014.

We found high heterogeneity in range and in energy consumption rate of BEVs depending, among others, on season (summer versus winter), driving patterns (speed and acceleration) and weather condition (temperature, rainfall, wind speed, snow). The mean predicted range (in km) of the BEVs used in the data is about 94 kilometers and the mean energy consumption per kilometer driven is about 181 watt hour (or about 0.40 DKK assuming 2.18 DKK per kilowatt-hour household price of energy). When compared with the values reported by car manufacturers, we found that the mean energy consumption rate is about 45 % (56 watt) higher and the range is about 27 % (about 36 kilometers) shorter than the BEV specification reported by manufacturers. Concerning the seasonal variation, we found that the mean range is shorter by about 25 % (about 26 kilometers) and the energy consumption rate (Wh/km) is higher by about 34 % (57 watt) in winter than in summer for the data we analyzed. That is, on average, each km driving in winter consumes 57 watt more energy than each km driving in summer. We also found that the main factors affecting the performance of BEVs are driving patterns (acceleration and speed) followed by winter season and other weather variables, more importantly, temperature. Moreover, we found that speed of driving and temperature have non-linear effect on energy consumption rate of BEVs, where driving under too low or too high of both variables results in high energy consumption rate per unit distance driven, ceteris paribus. Another important founding is that the battery depletion rate per unit distance driven is not constant, where 100 % charged battery drops very quickly (i.e., the percentage of battery depletion rate per unit distance driven is high), probably creating 'unnecessary range anxiety'.

The remaining section of the report is presented as follow. The data presentation and the methods used to compute the energy consumption rate of BEVs and to estimate the energy consumption rate of BEVs are presented in section two followed by the results from the data analysis in section three and a conclusion in section four.

[1] The number of drivers participated in the data collection were more than 758, but we considered only 758 drivers with data relevant for this report.

2. Data and Methodology

2.1. Data

2.1.1. Source

Four data sources were used for this paper: i) driving pattern data collected from 758 real-traffic BEV drivers covering 276,102 trips and about 2.3 million km travelled distance, which are extracted from GPS and data logger; ii) drivers household characteristics obtained from registered data and two stated preference surveys; iii) road characteristics collected from GPS data and maps matching and iv) weather data.

Clever A/S collected the driving pattern data from customers who have been driving BEVs for a period of 3 to 6 months in a project called ‘test-en-elbil’ (meaning ‘test an electric car’) in that individuals have been invited to rent and drive BEVs. The data were collected using GPS during the period from January 2012 to January 2014. Three fully battery electric car models, namely: Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev, were used for the test. The drivers were informed to use the BEVs as their primary means of travel during the test period. The age, gender and income variables of ‘drivers’ was also collected by Clever A/S during registration though we cannot be sure whether the BEVs had been driving by the costumers who were registered or whether the household members were also using the BEVs.

Detailed information about drivers’ household characteristics are obtained from two stated preference surveys administered before and after the drivers used the BEVs during the test period. The surveys were administered to find individuals preferences on the choices between BEVs and conventional cars (Jensen et al., 2013).

The weather information during the survey years, i.e., for the period from January 2012 to January 2014, are freely downloaded from the Weather Underground website, an internet-based weather information provider company (Weather Underground, 2014). Seasonal variables are obtained from the trip data.

2.1.2. Extraction of variables used in this paper

While only two variables, the distance of the trips and the corresponding energy consumption rate, are required for the computation of energy consumption rate and range of BEVs, more variables are required for the investigation of factors affecting energy consumption rate.

Variables related to income and demographic characteristics (age and gender) of drivers were collected during the registration process for testing BEVs and from the two surveys mentioned before. The drivers were from all over Denmark including men (56%), range of age from 18 to 73 (mean age 44 years) and from all income groups (where, about 48 % of them had yearly income between 450, 000.00 to 750, 000.00 DKK and only about 4 % of them earn income less than 230, 000.00 DKK). The data consists of household characteristics (such as income, number of family members, children, age etc.), housing asset ownership (house, car, etc.), work status, and other information including the respondents' preference on the choice between BEVs and conventional cars.

Variables related to driving patterns (i.e., driving speed and acceleration), date and time of each trip, the geographical coordinates of each trip, energy consumption rate in terms of percentage change in the battery level, distance and duration of each trip were extracted from the GPS information. The date and time of trips enabled us to obtain other variables such as rush hour trips, winter season and other variables.

Variables related to the features of the car are obtained from the manufacturers' websites and the Danish car registration for tax purpose. While the limited variation in car features that we have in the data does not allow us to analysis the effects of car features on energy consumption rate (since only three car models with similar specification were used), it helped us to investigate the effects of other variables on energy consumption rate by effectively controlling for variables associated with the car features.

Extracting detailed data about road characteristic is cumbersome since it requires measuring the road grade, congestion and non-congestion traffic stops, and so on. We use a dummy variable, whether the BEVs had been driving on highway, to account for road characteristics. Inability not to control for other road variables may result in omission variable bias, but we expect that the effect to be small since one of the main road variables affecting energy consumption rate – the road grade (Nam and Giannelli, 2005) – is less important in a flat Denmark. We also consider dummy for trips during rush hour and the interaction term between highway drive and rush hour to account for congestion.

Controlling for detailed account of weather information is complex since weather is dynamics across time and location even for a single trip. A driver could experience different type (rain, sunny, snow, etc.) and level of weather conditions along the way in a single trip, and accounting such detailed weather information is not only tedious but also less important since the changes in weather condition within a trip, where majority of routine trips are usually short in Denmark, could be marginal with infinitesimal effect on energy consumption. What previous studies used and that we use in this study are average values of main weather variables including temperature, air pressure, dew, humidity, wind speed and visibility as well as dummy variable for seasonal variables (winter). One major limitation in our weather variable is that we use the daily average temperature in Copenhagen area while the trips by BEVs were all over Denmark. This has two implications: i) since we consider the daily average temperature, we cannot explain the weather variation effect on the within-a-day variation in energy consumption rate of trips, if any; 2) since we use the weather information only around Copenhagen, there could be measurement error in weather variables if in case there is weather variation across different regions of Denmark. We also believe that the large sample size we have could make the errors small. The specific variables used in regression models are summarized in the table below.

Table 1: Description of Variables

Variable*	Description
Dependent variables	Energy consumption per unit distance (watt-hour/km)
	Speed of driving (km/h)
Independent variables:	
Driver Related	
Age (and its square)	Continuous in the range [18, 73]
Male	Dummy for gender (1 for male)
Income	Dummy for income (1 for income < 450,000 DKK)
Other variables	Education level, work type and flexibility, main means of commuting, etc.
Household characteristics	No. of family size, children, car ownership dummy, etc.
Road Characteristics	
Highway	Dummy for highway drive (1 if highway)
Rush hour	Dummy for any possibility of congestion (1 if the trip is between 7:00 - 8:30 or between 15:00 – 17:30)
Highway + rush hour	Interaction variable between highway drive and rush hour drive

Car features related	
The effects of car features on energy consumption rate are fully controlled since the BEVs were similar	
Weather variables	
Winter	Dummy for trips in winter (1 if the trip is during the months between Dec. and Feb.)
Year	Dummy for year of the trip (1 if 2012)
Winter + year	Interaction term for winter and year to account for across year seasonal weather differences
Temperature	Average daily temperature
Wind speed	Average wind speed (daily)
Air pressure	Average air pressure (daily)
Humidity	Average humidity (daily)
Rain	Dummy for whether there was rain (dummy = 1 if rain)
Snow	Dummy for whether there was snow (dummy = 1 if snow).
Time	Time of trip
Dew	Average dew (daily)
Driving pattern	
Speed of driving	Per trip mean speed
Acceleration	Per trip median acceleration
Trip distance	Continuous variable
Trip duration	Continuous variable
Departure time of each trip	
Energy consumption rate	Average of each trip

*non-linear effects are considered for some of the variables.

2.1.3. Data Clearing

Most of the 276,102 trips data are relevant that we use them directly. However, there are few (relative to the size of the data we have) observations that we are forced to drop due to errors made during data collection on one or more variables. To compute the energy consumption rate and the range, we had to drop 10969 trips with zero or missing reported energy consumption. We had to make judgments to exclude some trips as outliers by observing the reported energy consumption rate and trip distances. We further dropped more than 7300 observation with reported very high energy consumption rate (higher than 400 wh/km) and another about 12000 observations with very low energy consumption rate (less than 100 wh/km). We end up with 236,575 observations for the descriptive data analysis and 225,724 observations for regression analysis in that we further drop about 10851 observations with missing or outlier values of one or more explanatory variables.

2.2. Method

The paper used descriptive statistics, graphs and stochastic models to find energy consumption rate and to predict the range as well as to investigate factors affecting energy consumption rate variation of BEVs.

2.2.1. Methods to Measure the Performance of BEVs

There are two related ways of assessing the performance of cars in terms of energy consumption rate and range. The first method is to compute the energy economy (fuel economy for conventional cars), which is the distance travelled per a given amount of energy; for example, kilometers driven per a kilowatt-hour electricity power of the car battery (km/kWh). That is,

$$\text{Energy Economy} = \frac{\text{Distance Travelled (km)}}{\text{Power consumed (kwh)}} ------------------------- (1)$$

The energy economy gives the length of trip distance that can be travelled by kilo watt hour (kWh) of a BEV car battery. According to this measure, the higher the energy economy of a BEV is the better. That is, a higher energy economy means that we can drive long distance for a given power in the battery (or for a given energy cost) relative to a car with lower energy economy. For example, being able to drive 30 kilometers with 1 kWh of the battery power is better than being able to drive only 20 kilometers with the same 1 kWh battery power.

The other method used to evaluate the performance of cars is energy consumption rate (fuel consumption rate for conventional cars). It is the reprisals to the energy economy - the amount of energy used per unit distance. That is,

$$\text{Energy Consumption Rate (ECR)} = \frac{\text{Power consumed (Watt hour)}}{\text{Distance Travelled (km)}} -------------------- (2)$$

In this case, the lower is the better, i.e., covering a given trip distance with lower battery energy is, obviously, better than consuming higher energy to cover the same trip distance. For example, a BEV that consumes only 0.25 kWh per kilometer trip distance is better than a BEV that consumes 0.5 kWh per kilometer trip distance.

For the data we used, we observed only the percentage change in the battery level before and after each trip, not the amount of watt-hour used per trip. So, in order to compute the ECR in watt-hour per km terms, we had to multiply the percentage change of the battery power after the trip by the watt-hour of the car battery obtained from the specification of the cars, which is 16 000.00 watt-hour (or 16 kWh). For example, if we observe 100 % level of the battery before a trip and 50 % after a trip, then we multiply the percentage difference (100% - 50 %) by 16000 watt-hours to obtain the amount of watt-hour consumed by the trip, which gives 8000 watt-hour.

Another concern about the computation of the ECR is associated which trips to consider. Had the BEVs been driven continuously until a fully charged battery is completely used, then we could compute the ECR by simply dividing 16000 watt-hour of the BEV by the total trip distance. However, such cases are less likely to occur in real-world driving and we do not also observe in our data since the commuting trips in Denmark are short and since drivers may stuck on the way of their destination (before they arrive at a charging station for recharging) if they are to drive their BEVs until the battery power becomes zero. In such cases, we may compute the ECR in two ways. The first method is to consider the trip distance and corresponding energy consumed of each trip individually, and do any desired analysis accordingly. This way of obtaining ECR could give inaccurate values in situations where the battery depletion rate per unit distance is not constant across the different levels of the battery, for example, when the trip distance that we can drive by using 10 % of the battery power varies depending on the amount of battery power we have at the beginning of the trip say whether we have, 100 % and 40 % battery power. We found that the energy consumption rate at different level of the battery is not constant as can be seen from Figure 10, which could be a great concern particularly when the sample size is small. Of course, computing the ECR from each trip could not be a problem if BEV drivers use the BEVs either for long trips or if the BEV drivers use their cars until most of the battery power is used. Moreover, if the interest is to find explanations about the ECR, considering each trip ECR could be better. The second way of measuring ECR and the corresponding range of BEVs is to consider all trips traveled without recharging the battery so that it could be possible to find the ECR and the corresponding range that drivers experience from each recharging. The second method helps to capture any energy losses after the trip is completed. We use the second method to find mean values of ECR and the corresponding range, and we used the first method to investigate the factors that affect ECR.

Once we have the ECR, the range of a BEV can be computed as

$$\text{Range} = \frac{\text{The Power of a Fully Charged Battery (Wh)}}{\text{ECR (Wh/km)}} ------------------(3)$$

Note that the range could vary with either the capacity of the battery, the performance of the car or with both. Thus, a higher range doesn't necessary mean that the performance of the BEV in terms of energy consumption rate is better since the range difference could come from battery capacity difference (which usually comes with difference in the fixed cost of the battery). We should, thus, use either energy consumption rate or energy economy instead of range to compare different BEVs in terms of energy cost.

2.2.2. Models to Explain Energy consumption rate Variation

Explaining the factors that affect ECR (and range) of BEVs under different driving environments is relevant to consumers to choose appropriate cars that suits their demand under the driving environment they live in, and to manufacturers to distinguish and target different customers depending, among others, on the driving environments that customers are living in. This requires having appropriate model that helps to best estimate the magnitude and sign of the factors that affect ECR.

The models that have been used to estimate energy consumption of BEVs have been deterministic and usually include only few variables. For example, Duke et al. (2009) used the following model to estimate energy consumption rate of BEVs

$$P_c = ½(cdA\rho v^3) + MgRRV + P_a -------------------------(3),$$

where P_c is power to propel the car at 100 km/h, cd is the drag coefficient (a constant number that equals 0.25), A is frontal area of the car (m^2), ρ is air density (a constant number that equals 1.2 kg/m^2), V is speed (m/s), M is mass of the car (kg), g is gravity (9.8 m/s^2), RR is rolling resistance (a constant number that equals 0.008) and P_a is power for auxiliary power required for lights, breaks etc. (Duke et al., 2009).

According to this model, energy consumption rate of a BEV is the same regardless of the weather condition, the drivers' characteristics and other factors, which is not the case in the real-world situation as energy consumption rate can be significantly affected by a number of factors as we discussed before.

Since the data used in this paper is (unbalanced) panel data in that each BEV driver was observed for overtime, we used individual effects model that is used by Zahabi et al. (2014) in their fuel consumption rate estimation for conventional and hybrid cars.

$$ECR_{it} = X_i\beta + W_{it}\alpha + Y_{it}\delta + Z_{it}\gamma + f(\mathrm{X, W, Y, Z}) + \phi_i + \upsilon ----------------------(4)$$

ECR_{it}: is the energy consumption rate for a trip by individual i at time t.

X_i : is a row vector of the car features used by individual i. Since the cars used in our data are similar, we don't include these variables in the regression model.

W_{it} : is a row vector of weather variables that could vary across individuals and across time within an individual

Y_{it} : is a row vector of road variables that could vary across individuals and across time within an individual

Z_{it} : is a row vector of the driver's household characteristic variables could that vary across individuals and across time within an individual

$f(\mathrm{X, W, Y, Z})$: denotes any possible interaction terms between the variables stated before

α , β , γ , δ : are a column vector of parameters

ϕ_i : is a time-invariant unobserved (to the researcher) effect that could vary across individuals. For example, it could be the car treatment (greasing, parking place, etc.) that could vary across individuals but not within an individual.

υ : is the idiosyncratic error term

The choice of the appropriate model mainly depends on how the unobserved effects, ϕ_i , is related to the explanatory variables, where the random effects model is preferred to fixed effects model when ϕ_i is uncorrelated with explanatory variables; whereas the fixed effects model in that ϕ_i is removed by time-demeaning each variable in the equation (4) is preferred otherwise (Wooldridge, 2010). Having found that the fixed effects model is preferred to random effects model by Hausman test (we conducted the non-robust test). Moreover, the fixed effects model could also better controls for the time-invariant drivers' and their households' characteristics by removing them due to the demeaning, since these variables may involve measurement error as the BEVs could be driven by more than one of the household members that we cannot identify in the data we have. See Wooldridge (2010) for detail account of the models.

3. Result

In this section, we present the results from the data analyses. The main results presented in this section include descriptive results about the trips, energy consumption rate (by different category) and regression result explaining energy consumption rate variation.

3.1. Overview of Trips by BEVs

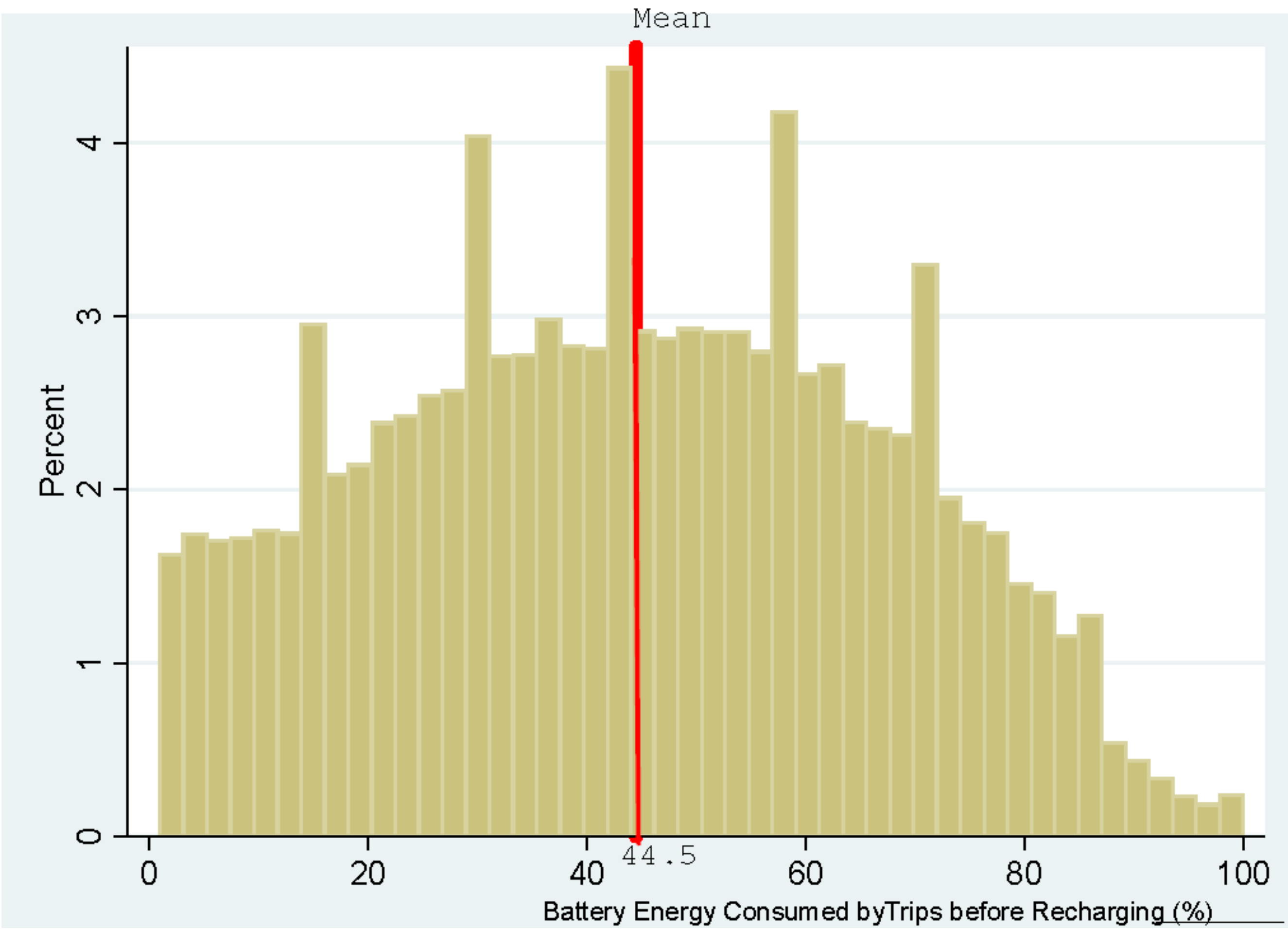
In this section we present overview of trips by BEVs to observe the time-pattern of trips and the distances travelled by BEVs. The results are presented along with similar results obtained from the Danish Travel Survey data – a large travel survey collected on annual bases by Department of Transport, Technical University of Denmark.

On average, each driver had 307.1 trips during 90.7 average days of follow up that gives a mean of 3.4 trips per day by each driver. Related to the trip distance, BEVs were used for short trips; about 50 % of trips were less than five kilometers, and trips longer than 50 km were only about 1 % of the total trips we observed as can be seen from the histogram given in Figure 6. One reason for this could be the overall short commuting trips in Denmark; about 39 % of Danes commuted less than five km in 2013 (Denmark Statistics, 2014).

Related to frequency of charging, a lion share of individuals did not charge the batteries of BEVs upon the arrival from each trip: the frequency of charging observed in the data is 21.4 % of the total number of trips. This means that, on average, BEV drivers had been charging their car after using the car for about 4.7 trips. One reason for this low frequency of charging could be because of the short trips that BEV drivers had and/or could be because of lack of charging facilities at each destination of trips.

However, the infrequent charging relative to number of trips doesn’t mean that the drivers had been using the BEVs until the fully charged car battery is flat. The data shows the other way: the mean and median levels of battery percentages after which the battery had been recharged are about 44.5 and 44 respectively. That is, the drivers had been recharging their BEVs after using about 44.5 % of the battery power. Surprisingly, 26 individuals drive the BEVs until the battery power is completely used, but unfortunately we do not observe what happened to these drivers, i.e., whether they stuck on the way to their destination before they arrive at a charging station. Further details about the distribution of the amount of battery used for trips after which the battery is recharged again for the next trip can be observed from the histogram given in Figure 1.

Figure 1: Battery Power Used (in %) by Trips before Recharging for the Next Trip

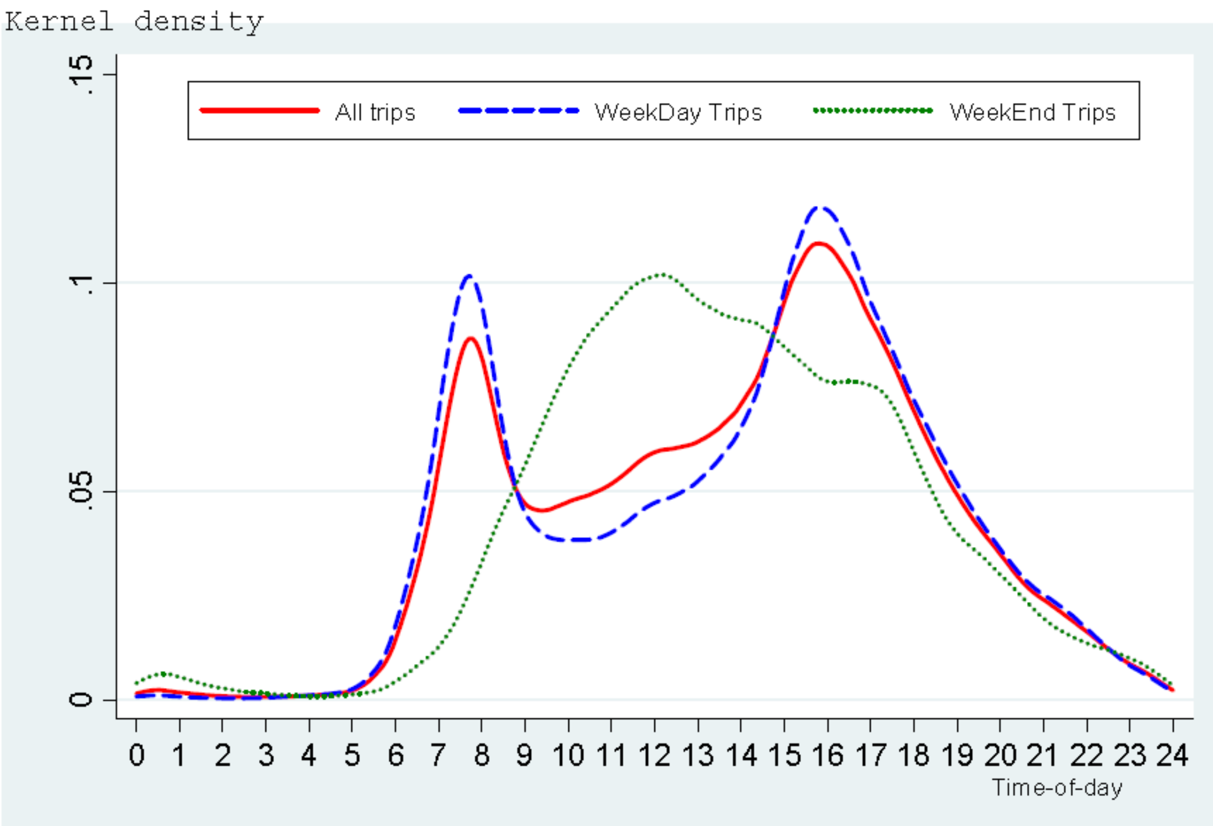


The first eye-catching observation in the above figure could be the five highest bars that denote higher frequency than the neighbor bars. This could be because of routine trips by one or more drivers who could have been recharging their BEVs after having a routine trip. Another interesting observation from the figure could be that there were drivers (26 in number) who drove BEVs until the battery power was completely used though we don't observe what happened to these drivers afterwards, i.e., whether the battery became flat before they arrive at a charging station. We can also observe that there are a considerably large number of cases that the BEVs drivers had been recharging their cars after using only a small percentage of the battery power.

The time-of-day trip patterns by BEVs could be also of interest; for example, to observe whether BEVs had been used for daily routine trips in that, we expect trips by BEVs to have similar time pattern to the general population. One way of observing this could be to consider the frequency of trips at rush hours. The time-patterns of trips by BEVs is presented in Figure 2 allowing with the time-pattern of trips from the Danish

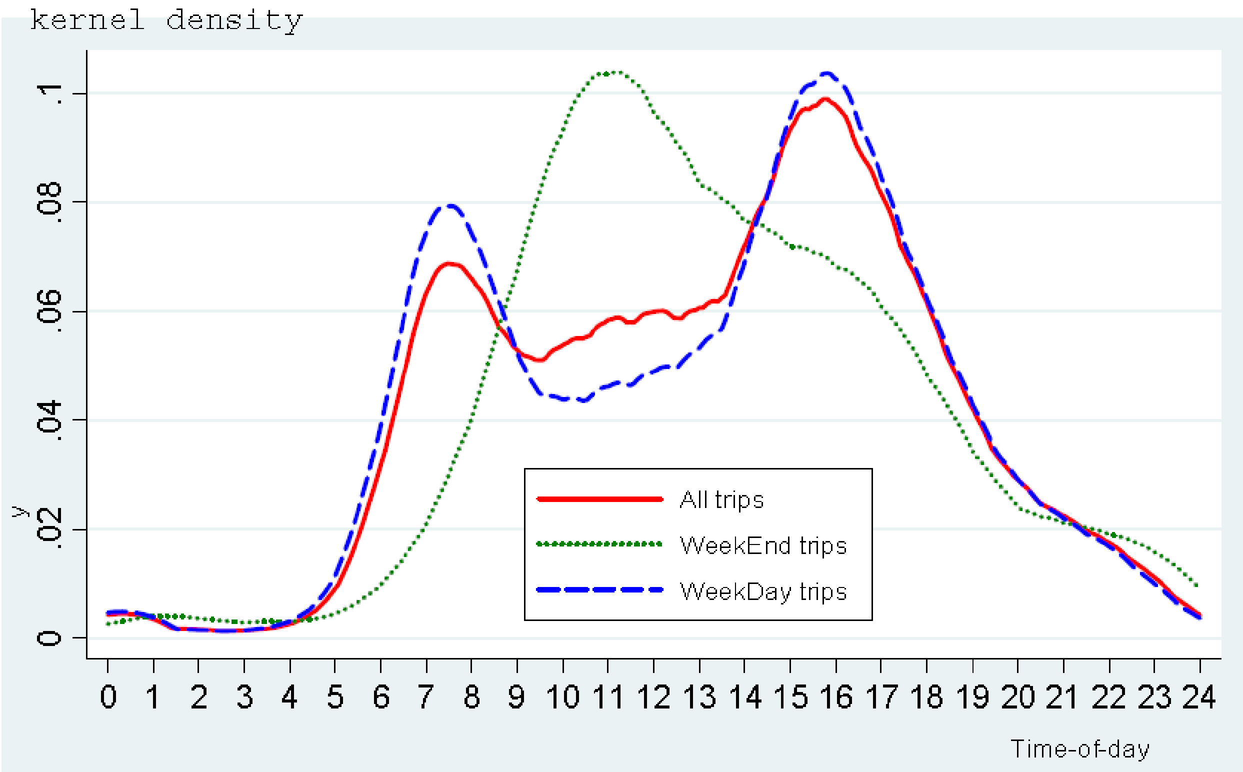
National Survey presented in Figure 3. As it can be clearly observed from the figure, BEVs have been driven more frequently during rush hours.

Figure 2: Departure Time of Trip by BEVs, Kernel Density



Another way of observing whether BEVs have been used for routine trips is to compare the trip patterns by BEVs with the trip pattern obtained from the general population, which we do with the data obtained from the Danish National Travel Survey. As we can observe from Figure 2 and Figure 3, trips by BEVs and the trips sampled from the general population have similar time pattern in that there are high frequency of trips during rush hours of weekdays, and different weekend and weekday trip patterns in both types of trips. This could indicate that, similar to conventional cars, BEV had been used for routine trips at least for the data that we used.

Figure 3: Departure Time-of-day of Trip, Kernel Density from National Travel Survey

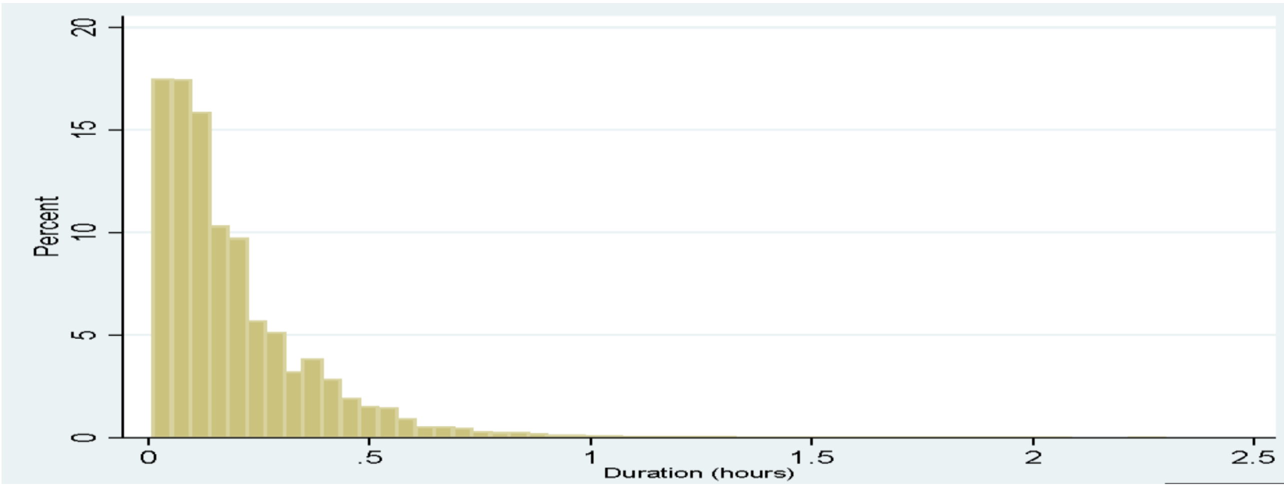


Source 1 Compiled from the Danish Travel Survey Data for Passenger Cars (2013)

The duration of trips by BEVs could be also an interest to know. We present the duration of trips by BEVs in Figure 4 along with the duration of trips obtained from the Danish Travel Survey presented in Figure 5[2]. The two figures reveal that 1) overall, most of the trips in Denmark have been taking less than half an hour; 2) a lion share of trips both by BEVs and conventional cars have been taking less than 30 minutes. However, the trips by conventional cars have longer and thicker tail than trips by BEVs, i.e., BEVs have been used less frequently for trips that took longer than an hour when compared with trips by conventional cars. We can also observe the trip distances by BEVs in Figure 6.

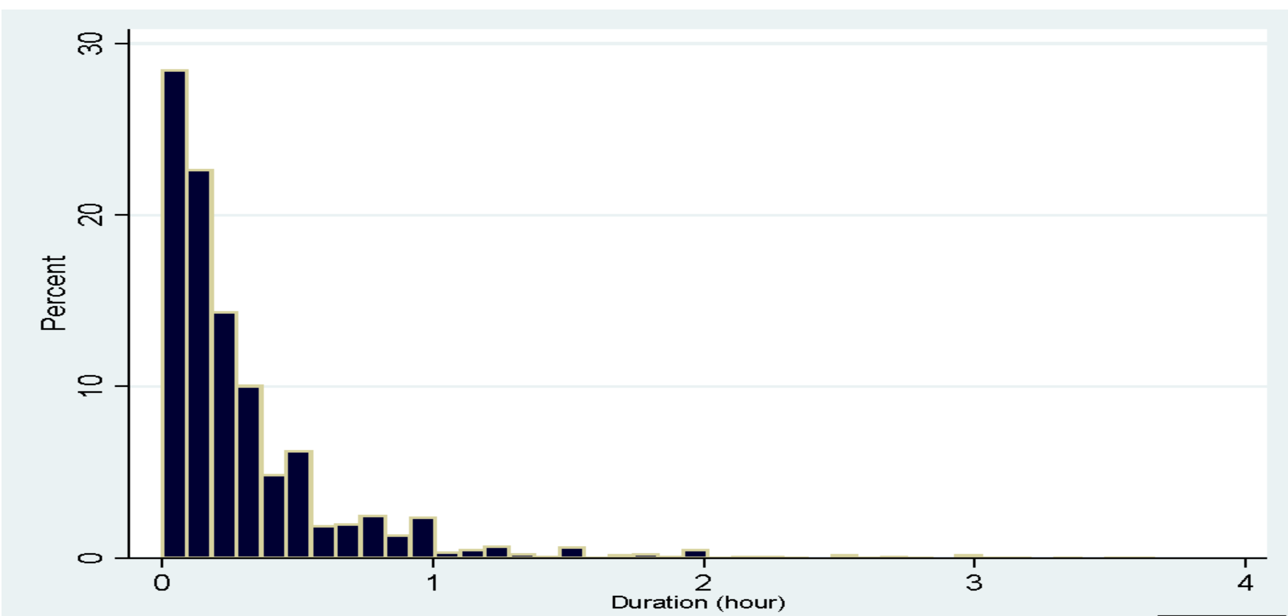
[2] Please note the scale difference of both the horizontal axis (the duration (in hour)) and the vertical axis (percentage) whenever comparing Figures 4 and 5.

Figure 4: Duration (in hours) of Trips by BEVs



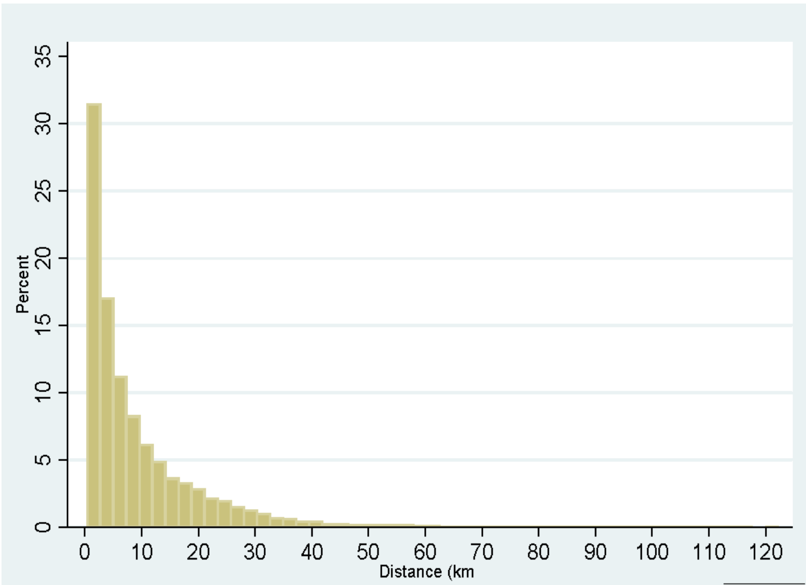
Note: The graph shows the duration of trips by BEVs. The horizontal axis denotes the duration (in hour) of trips and the vertical line denotes the percentage of trips (out of 100 %) corresponding to each duration time. We can observe that more 50 % of the trips by BEVs took less than 15 minutes.

Figure 5: Duration (in hours) of Trips (from the Danish National Survey)



Note: (Source: Compiled from the Danish National Survey Data). The graph shows the duration of trips by conventional passenger cars (excluding vans) for the year 2013. The horizontal axis denotes the duration (in hour) of trips and the vertical line denotes the percentage of trips (out of 100 %) corresponding to each duration time. We can observe that more 50 % of the trips took less than 15 minutes.

Figure 6: Trip Distance Driven by BEVs



Note: (Source: Compiled from the BEV data). ***The graph shows the length of trips (in km) driven using BEVs. The model (most frequent) trips were less than 5 km.***

3.2. Energy consumption Rate and Range of BEVs

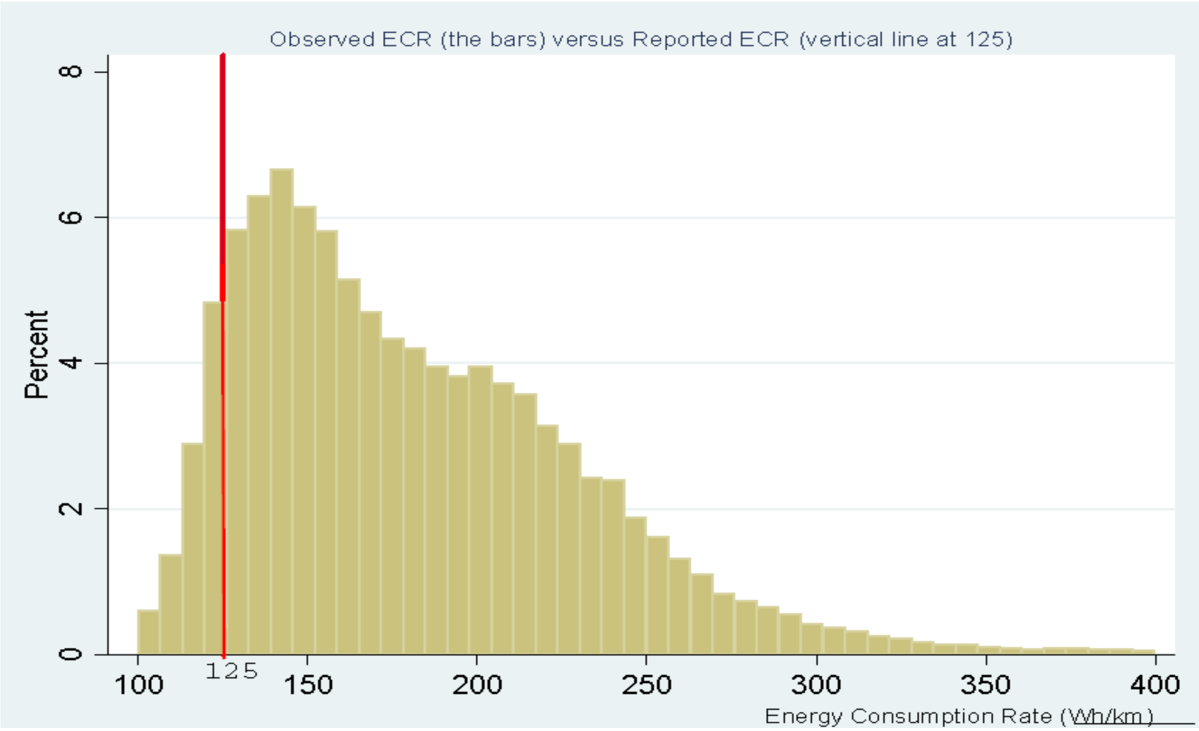
The real-world energy consumption rate and the corresponding range of BEVs are of the most important variables that stakeholders of BEVs in general, and, in particular, buyers of BEVs need to know as there is range anxiety problem associated with longer time of charging and limited range of BEVs. As stated before, the lower is the energy consumption rate (which implies a longer range), the better the BEV is since this means that the BEV user can drive a given trip distance at low energy cost, or the BEV user can drive longer distance (i.e., have longer range) for a given level of battery power cost.

In this section, we present the energy consumption rate that is used to evaluate the performance of BEVs relative to the value reported by car manufacturers. Since energy consumption rate could vary with the length of trips, weather condition and driving style, it could be relevant to present energy consumption rate under these different categorizes and the overall energy consumption rate under the Danish driving environment. For example, BEV buyers living in different weather conditions may have to buy different battery power capacity BEVs depending on the duration and intensity of winter.

The overall energy consumption rate (Wh/km) and the corresponding distance (range) that can be covered by a fully charged battery is presented in the following histograms along with vertical red lines denoting the mean energy consumption rate (125 Wh/km) and the range (130 km) obtained from the specification of BEV by manufacturers[3]. The energy consumption rate and the range are obtained using equations 2 and 3 given before.

[3] Note that we considered all trips with expected range shorter than 40 km and longer than 160 km as outliers. Considering the whole data without excluding these outliers doesn't affect the mean ECR and the range (only increased the ECR by 1.3 and decreased the range by 0.2 km), but it affects the minimum and the maximum values.

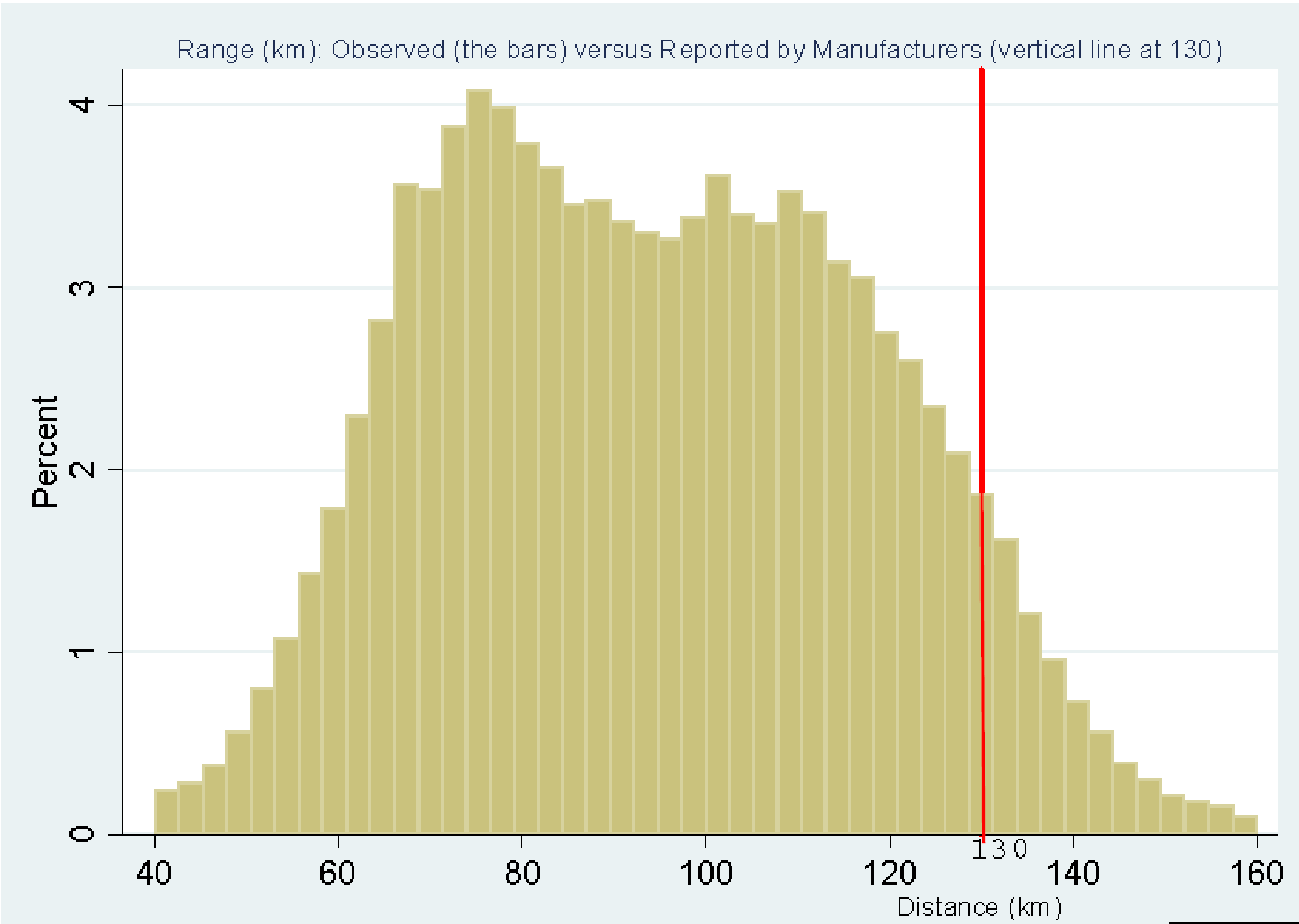
Figure 7: Observed Versus Predicted Energy consumption rate of BEVs



Note: ***The energy consumption rate is computed from the trip data by dividing the sum of energy consumed (in watt hour) by the corresponding sum of distance (in km) for trips travelled without recharging the car battery. The vertical line at 125 watt-hours denotes the mean energy consumption rate obtained from the cars' specification. Majority of the bars lying to the right of the vertical line at 125(Wh/km) denotes that BEVs consumed higher energy per unit distance than stated in the specification by manufacturers.***

A number of interesting points can be noted from the histograms presented in Figure 7 and 8. The first pinpoint to note from the histograms is that a lion share of the observed energy consumption rate lies to the right of the mean energy consumption rate obtained from the BEV's specification. This means that, BEVs consume more energy per unit distance than what is reported by manufacturers, resulting in a lower range for the majority of the observations than the mean range (130 km) obtained from Citron C-Zero specification.

Figure 8: Observed Versus Predicted Range of BEVs



Note: The range denotes the total distance that can be covered by a fully charged battery. It is computed using Equation 3 given before. Most of the observations are to the left of the range reported at the car specification (denoted by a vertical at 130 km) shows that the actual range of BEVs is less than the reported range, at least for the data we used.

This difference in energy consumption rate between what is found by car manufacturers and what is revealed in our real-world data could be because the manufacturers usually test the BEVs in continuous driving until a fully charged battery is completely used (Seredynski P. and O'Dell J., 2013) in that the energy used to overcome the inertia force to propel a parked car and the energy used to cool down a propelling car for each real-world short trips is saved in manufacturer testing. Moreover, the drivers used to test BEVs are usually experienced when compared with the general population in that the energy loss associated with any lack of experience in the real-world driving could be also saved in the case of car manufacturers' case. Huo et al. (2011) also found about 15.5 % fuel economy difference between real-world drive and sales-weighted reported fuel economy among conventional cars in China.

Another point to note from the histograms is the high variability in energy consumption rate and the corresponding range for the data we used for this paper. This indicates that there are factors that affect energy consumption rate of BEVs significantly, something that we come to it later. We also presented the energy consumption rate and the corresponding range in Table 2 below.

Table 2: Energy consumption rate and Range by BEVs

	Mean	**5p**	**25p**	**Median**	**75p**	**95p**	**St. dev.**	**No. obs.**
Energy consumption rate (Wh/km)	181 (125)[*]	120	142	171	212	272	50	41965
Range (total distance that can be driven by fully charged battery)	94 (130)	134	112	93	75	59	24	

Note: 'p' denotes percentile, '*' Values in the parenthesis denote the values obtained from Citron C-Zero specification. Also note that the number of observations used to compute the values in the table are much less than the total number of relevant trips. This is co because we added up trips traveled without recharging by the same driver together to get better prediction of the range as discussed before.

The variation in ECR observed in the figure before can be also observed in the table given above. The 5^{th} percentile (the value below which 5 percent of the observations have lower values) ECR is 120 wh/km and the corresponding range is 134 kilometers, whereas the 95^{th} percentile ECR is 272 wh/km, and the corresponding range is 59 kilometers.

The cost of a trip for a BEV driver can be found by multiplying the watt hour consumed to cover the trip by the price of electricity at the charging station, and the computed value can be used to compare BEVs with conventional cars in terms of fuel (energy) consumption. For example, considering the mean value of energy consumption rate given above and the household price of electricity (2.18 DKK per KWh = 0.00218 DKK per Wh) (Dong energy, 2014). A 50 km trip by BEV costs about

$$50\ (km)\ *\ 181\ (Wh/km)\ *0.00218\ \ (DKK/Wh)\ =\ 20\ DKK\ ;$$

whereas it cost about 27.8 DKK by a petrol passenger car (using mean fuel economy of 4.62 liters per 100 km obtained from Denmark Statistics, and petrol cost of 12 DKK per liter), indicating that a BEV driver could save fuel cost of about 7.8 DKK per 50 km trip when compared with a conventional car, ceteris paribus.

i) Energy consumption rate by Trip Distance

Since driving patterns could vary with the trip distance (Fosgerau, 2005), which in turn could affect energy consumption rate (Ericsson, 2001), it is relevant to consider energy consumption rate at different trip distances so as to know for which type of trips are BEVs more convenient in terms of energy cost saving. In this paper, we consider energy consumption rate and the range by divided trips into three based on the trip distance: short trips (trips not less than 2 km), medium trips (between 2 and 10 km) and long trips (trips longer than 10 km). We somewhat considered the commuting distances of Danes to divide trips as short, medium and long; one can also follow different criterion. The result from the analysis is presented in the following table.

Table 3: Energy consumption rate and Range of BEVs by Trip Distance

	Short Trips (< 2 km)		**Medium Trips (≥ 2 km & < 10 km)**		**Long Trips (≥ 10 km)**	
	ECR (Wh/km)	Range (km)	ECR (Wh/km)	Range (km)	ECR (Wh/km)	Range (km)
Mean	223	82	183	96	166	102
5 percentile	112	143	111	144	114	141
25 percentile	162	99	136	117	134	119
Median	209	76	169	95	159	101
75 percentile	281	57	222	72	192	83
95 percentile	366	44	298	54	238	67
Standard dev.	79	30	59	28	39	23
No. obs.	54, 161		108, 605		73, 809	

***Note: Energy consumption rate (ECR) and range by trip distance computed using each trip instead of aggregating trips traveled without recharging since our interest here is to access the variation in ECR depending on trip distances. The table shows that the mean energy consumption rate is higher and the range is shorter for short trips than long trips*.**

Table 3 clearly reveals that the mean ECR decreases (and the mean range increases) with trip distances. For example, on average, short trips consume about 57 more watt hours per km than long trips. Similarly, considering the 95 percentile highest energy consumption rates, drivers who used BEVs for short trips had a 23 km lower range than drivers who used BEVs for trips longer than 10 km, i.e., an equivalent energy that could enable to drive about 23 km in the 95 percentile higher energy consumption rate is lost due to the shortness of trips. The difference is observed in all but 5th percentiles, and is statistically significant both by a parametric t-test (mean equality test) and nonparametric Mann-Whitney test (equality of values of the two distributions test): the p-value =0.0000 for both tests rejecting the hull hypothesis of equality of values.

ii) Energy consumption rate by Season (winter vs summer)

The table below reveals that energy consumption rate is higher and the range is shorter in winter than in summer: each km driven in winter consumes, on average, 57 watt-hours (about 34%) more power than in summer, and there is about 26 km difference in range. The difference is observed in all percentiles, and is statistically significant both by a parametric t-test and nonparametric Mann-Whitney test: the p-value =0.0000 for both tests rejecting the hull hypothesis of equality of values. A similar result, but about hybrid EVs, is by Zahabi et al. (2014) who found about 20 % fuel efficiency impact of the winter season in Canada.

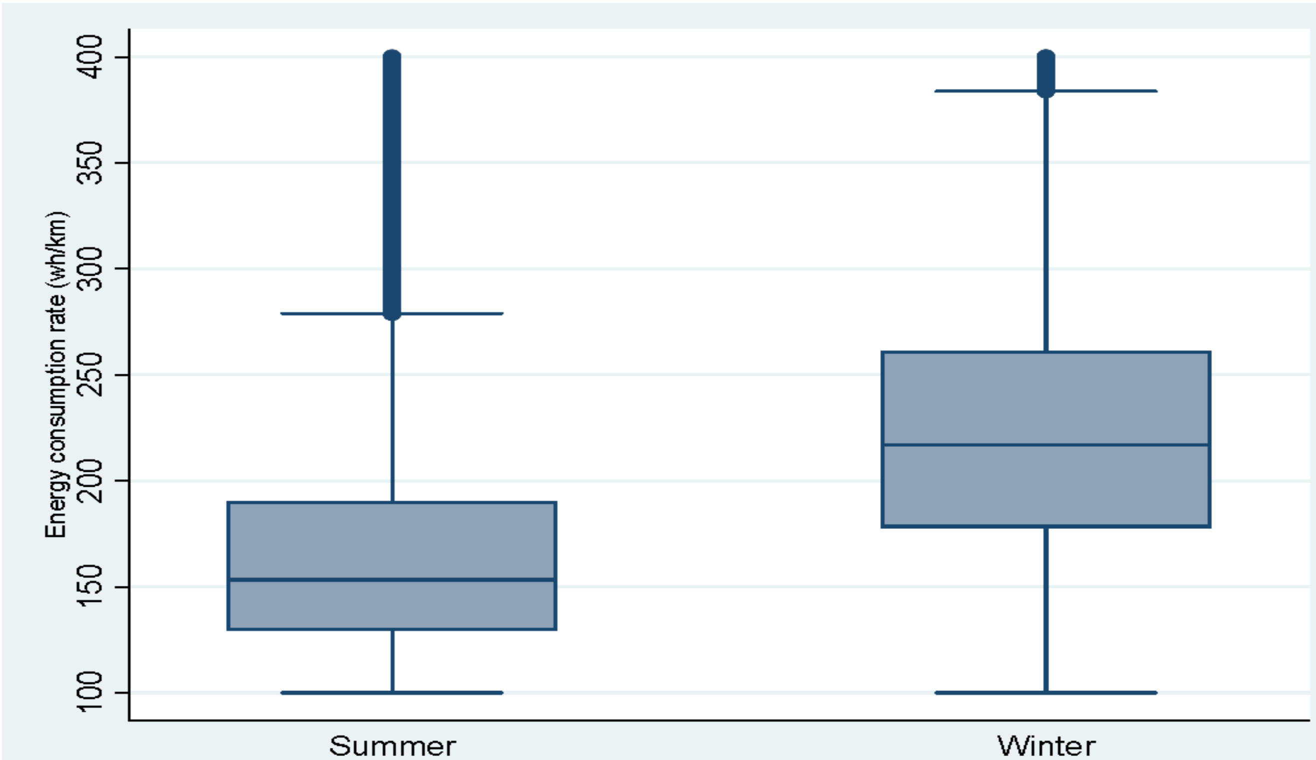
Table 4: Energy consumption rate and Range by season

	Summer trips		**Winter trips**	
	ECR (Wh/km)	Range (km)	ECR (Wh/km)	Range (km)
Mean	168	103	225	77
5 percentile	109	146	133	120
25 percentile	130	123	179	90
Median	154	104	217	74
75 percentile	191	84	262	61
95 percentile	280	57	347	46
Standard dev.	54	27	63	22
No. obs.	157,676		78,899	

***Note: Energy consumption rate (ECR) and range by trip distance computed using each trip. The table shows that energy consumption rate is higher and the range is lower for trips in winter than for trips in summer*.**

The energy consumption rate difference between summer and winter can be also noticed from the following Box-and-Whisker Plot.

Figure 9: Box-and-Whisker Plot of Ssummer and Winter ECR



Note: Box-and-Whisker plot that display variations in a sample of population non-parametrically. The filled-in boxes present the interquartile range with the intermediate line denoting the median. The wishers, denoted by horizontal lines, help to observe outliers. Energy consumption rate in summer is clearly lower than in winter.

iii) Energy consumption rate and Range by Route Type

The effect of road characteristics on fuel economy of conventional and hybrid cars is well documented in the literature. See, for example, (Brundell-Freij and Ericsson, 2005; Ericsson, 2001b; Zahabi et al., 2014). We presented energy consumption rate and range differences between highway and non-highway drives.

Table 5: Energy consumption rate and Range by Route Type

	Trips on Highway		**Trips not on Highway**	
	ECR (Wh/km)	Range (km)	ECR (Wh/km)	Range (km)
Mean	174	96	187	94
5 percentile	121	132	111	144
25 percentile	145	111	138	116
Median	168	95	172	93
75 percentile	198	81	223	72
95 percentile	243	66	318	50
Standard dev.	39	21	63	29
No. obs.	16,369			210,984

Note: we considered each trip instead of aggregating trips traveled without recharging the car battery since there was large number of cases that trips were conducted both on highways and non-highways without recharging in that we cannot aggregate the trips conducted without recharging and separate by route type.

Table 5 reveals that while the 5th and 25th percentiles of ECR of trips on non-highways are lower (and the corresponding ranges are longer) than for trips on highways, the mean, median, the 75th percentile and 95 percentile of ECR of trips on highways are lower (and the corresponding ranges are longer) than for trips on non-highways.

It is very important to note that the observed differences in ECR and the corresponding ranges by trip distance (short, medium and long), season (winter versus summer), and route type (dummy for highway) that we observed in Tables 3 to 5 are average comparisons that without considering the possible impacts of other variables on ECR. This means that the values that we observed above could be larger or smaller if we control for other confounding factors that are correlated with these variables and that affect ECR. For example, the ECR variation by route type that we saw in Table 5 could be because of trip distance differences (highways trips could be longer), driving pattern difference by route type, and so on. Therefore, it is importance to conduct further analysis to find the 'real impacts of each factor' by controlling for other confounding factors that affect ECR. For this end, we conducted regression analysis that is presented in later section of the paper.

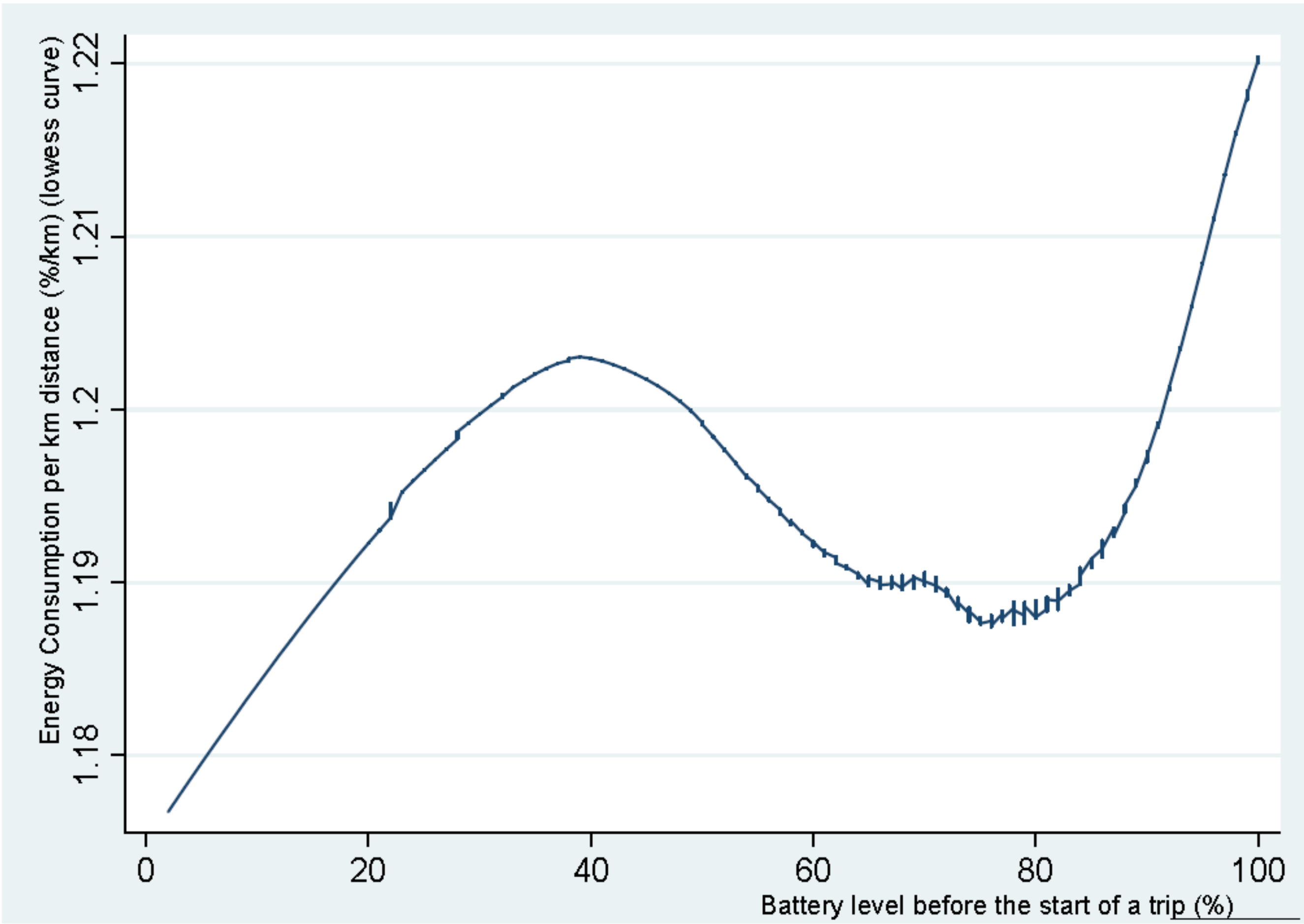
3.3.The Battery Depletion Rate (Energy Consumption Curve)

Does a fully charged battery power depletes at a constant rate per unit distance or is there any variation depending on the initial level (status) of the battery power, which is usually displayed on ‘gauges’ in percentages (not in terms of kWh) to the driver? Stating in other words, can we drive equal distance using 10 % of the battery power when the initial (before trip) powers are 100 % and 20 %? This section has an answer.

How battery power, presented to drivers in percentages, depletes per unit distance could be of great interest, at least to let the BEV drivers know the range they can cover by the battery power they left with, ceteris paribus. It is relevant for the BEV drivers to know whether they can drive the same distance with say, 10 %, of the battery power left as they drive by using the last 10 % of the battery power they used. If the depletion of the battery power is constant, then it could be easy to predict the range that the driver could cover by the remaining battery power displayed in the car. However, the rate of depletion of the battery power per unit distance varies with the initial battery power as we can observe from the following Figure 10. The graph is a nonparametric locally weighted scatterplot smoothing estimation (usually abbreviated as lowess) obtained by running-line least-squares smoothing with 0.8 bandwidth (i.e., 80 % of the observation is used to estimate each point on the curve). It shows that the depletion rate of the battery power is a polynomial function, where the rate of depletion per unit distance is very high (with mean estimated value higher than 1.22 per km driven) when the battery power is about 100 % charged (probably resulting in range anxiety to new drivers that could affect their demand for BEV), declines at a higher rate as the battery power decreases until it reaches a local minimal of about 1.173 % battery power consumption per km distance traveled when the battery power is about 77% left. Then, the battery depletion rate gradually increases until it reaches local maximal of 1.123 % battery power consumption per km distance traveled, after which the depletion rate declines gradually.

Note that the graph is drawn without controlling for any confounding factors that could affect the energy consumption rate per unit distance. It is a mean estimation.

Figure 10: Energy Consumption Curve (Battery Power Depletion Rate per Unit Distance (%/km))



Note: locally weighted scatterplot smoothing estimation of the battery power depletion rate per km distance traveled.

This graph has to be clearly presented to BEV drivers so that they could have a better approximation of the range that they can travel with the battery power they left with; otherwise BEV drivers, particularly those who are new to BEVs, could 'unnecessarily panic' when they observe that a fully charged battery drops very quickly after having only a short drive.

3.4. Explaining Energy consumption rate difference

In this section, we present regression results intended to explain the energy consumption rate variation that we observed in Figure 7. The relevant model we use to estimate ECR that is favored by (the non-robust) Housman test (a test that compares the fixed and random effects models) is the fixed effects model.

The table reveals that the model explains about 70 % of the energy consumption rate variation between drivers, about 28 % of the variation within drivers and about 41.5 % of the overall energy consumption rate variation observed in the data.

As we can observe from the result presented in Table 6, most of the explanatory variables are individually statistically significant and have the expected sign, except dummy for rush hour drive that is marginally significant and has an unexpected sign.

The most important determinants of energy consumption rate of BEVs are found to be driving patterns (acceleration and speed, both non-linearly) followed by seasonal variation (a winter dummy), temperature (non-linearly) and road type (dummy for highway drive). Recall that the lower the energy consumption rate is the better and, thus, explanatory variables with statistically significant and negative signs indicate that energy consumption rate declines as these variables increase, i.e., the performance of BEVs energy cost saving increase, ceteris paribus.

Table 6: Explaining Energy Consumption rate (dependent variable: ECR (Wh/km))

Explanatory Variables	Coefficient	Std. Err. (cluster robust)	p-value
Speed of driving (average)	-19.00049	0.3645908	0.0000
Speed of driving square	0.7605597	0.0152035	0.0000
Acceleration (median)	55.52145	7.155919	0.0000
Acceleration square	27.82806	9.149586	0.0020
Trip distance	-1.109875	0.0623994	0.0000
Trip distance square	0.0096741	0.0009548	0.0000
Winter (dummy: 1 if the season was in winter)	12.94529	1.13063	0.0000
interaction term between winter and trip distance	-0.6001109	0.0498611	0.0000
Highway (dummy: 1 if highway drive)	6.246636	1.022883	0.0000
Rush hour (dummy: 1 if the trip was at rush hours of traffic)	-0.5655404	0.3274052	0.0840
Battery level measures at the start of the trip	3.401139	0.2061548	0.0000
Battery level square	-0.0564246	0.0033213	0.0000
Battery level cube	0.0002938	0.0000169	0.0000
Temperature (daily average)	-2.209058	0.1821556	0.0000
Temperature square	0.0787949	0.0051118	0.0000
Wind speed (average)	0.5412278	0.0231944	0.0000
humidity (average)	1.102235	0.0487547	0.0000
Snow (dummy: 1 if there was snow on the day of the trip)	1.38622	0.5781293	0.0170

Visibility Average	0.454365	0.0460654	0.0000
Dew (average)	-2.912585	0.195021	0.0000
constant	135.4886	6.378105	0.0000
R-sq: Within = 0.2810	sigma_u = 20.025775		
Between = 0.7019	sigma_e = 44.810975		
Overall = 0.4150	rho = 0 .16646845		
No. Obs. = 225, 724			

The regression result reveals that speed of driving has non-linear (U-shaped) effect on ECR. This could be so because speed of driving could affect ECR in two ways. First, higher speed reduces energy consumption rate (which is computed by dividing the total distance of a trip by the total energy consumed for that trip) by reducing the duration of the trip time. Second, higher speed increases energy consumption rate by increasing the energy used to propel and keep the car running, i.e., speed increases the energy consumption per unit of time as can be clearly noted from the scatter plot presented in Figure 13. These two conflicting effects of speed of driving on ECR indicate that there could be a threshold level of speed that minimizes energy consumption rate unless and otherwise one of the two effects always dominates the other effect. A locally weighted scatterplot smoothing estimation (lowess) presented in Figure 11 confirms that there is a threshold level of speed of driving that minimizes energy consumption rate. Similar graphical result is found among conventional and hybrid cars (Zahabi et al., 2014). However, previous papers, for example, by Zahabi et al. (2014), did not control for the non-linearity effect of speed of driving on energy consumption rate by assuming that energy consumption rate increases at a constant rate with speed of driving, which means that increasing driving speed from say, 1 km/h, to say, 21 km/h, has similar effect on energy consumption rate to increasing the speed of driving from say, 70 km/h to 90 km/h. However, as our result confirms, speeds of riving has non-linear effect, and the model predicts that the energy saving speed of driving is 12.5 m/s (equivalent to about 45 km/h), which is lower than the prediction we obtained based on the locally weighted scatterplot smoothing estimation presented in Figure 11 (54 km/h[4] overall, 50 km/h), and is lower than the optimal speed for conventional vehicles, about 65 km/h, found by El-Shawarby et al. (2005). We can observe from Figure 12 that about 85 % of the trips were driven at speeds either faster or slower by a minimum of 3.4 km/h than the energy saving speed of driving predicted in our model.

Table 6 reveals that acceleration is the most important determinant of ECR. Acceleration increases ECR at an increasing rate, ceteris paribus. A number of studies also found significant impact of acceleration on fuel

[4] Note that the lowess estimation is an average estimation that doesn't control for other factors.

consumption rate of conventional and hybrid cars. See, for example, Zahabi et al. (2014). Besides to testing the impact of acceleration on ECR of BEVs, the contribution of this paper is to find the non-linearity of the impact.

Winter season has also a considerable impact on ECR. The regression result shows that each kilometer distance driven in winter consumes about 13 watt-hours more energy than summer trips even after controlling for the daily average temperature and other weather variables presented in Table 6. Note that since we already included many of the weather variables that vary over season (summer versus winter) individually in the regression model, the real impact of the winter variable is higher than 13. The total effect of the winter season can be obtained by aggregating impacts of all the weather variables evaluated at mean values. By substituting the mean values for weather variables in winter and summer seasons and taking the difference, we found about 62.5 watt hour difference between winter and summer in terms of ECR (7.5 watts higher than the mean energy consumption difference that we saw in Table 4) implying that driving BEVs in winter consumes about 62.5 watt more energy per kilometer distance than driving in summer. Thus, the winter dummy variable presented in the table should be interpreted as a variable denoting winter variables, such as snow on the street, which we do not control for.

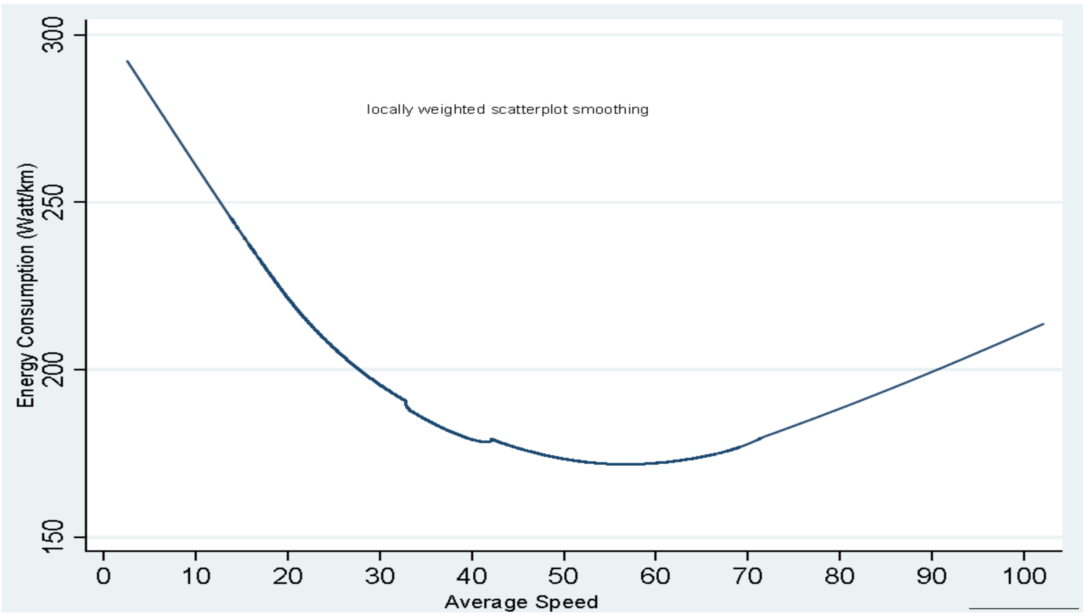
Another interesting result is the non-linear (U-shaped) effect of temperature on the energy consumption rate. Driving both under too low or too high temperature rates is not good in terms of energy consumption rate. We found that the level of temperature at which energy consumption rate is the minimum is about 14 ^{0}C, ceteris paribus. Among the explanations for higher energy consumption rate associated with temperature could be because of additional energy consumption for warming the car (when the outside temperature is too cold) and for cooling the car (when the outside temperature is too warm). Lohse-Busch et al. (2013) found a non-linear effect of temperature on ECR under a controlled lab experiment. Zahabi et al. (2014) also found a linear impact of temperature on fuel consumption rate of conventional and hybrid cars.

Route type (dummy for on highway drive) is another variable with statistically significant and positive impact on ECR of BEVs. As we can observe from the table, driving on highways increases the ECR by about 6 watt-hours per km distance driven. Recall that we observed in Table 5 that highway drive mean ECR is higher by about 13 watt-hours than non-highway mean ECR drive. However, that difference drops to 6 when we control for other factors that could be confounded with highway drive and affect ECR resulting in spurious result. The mean ECR difference between highway and city drive is even higher, about 47 watt-hours, in USA (EPA, 2014).

Note also that the initial level of the battery has a polynomial (of degree three) ‘effect’ on ECR, which features battery power depletion rate that we saw in Figure 10. Other variables including wind speed, a dummy for whether there was snow on the trip day, humidity, and so on also affect ECR significantly.

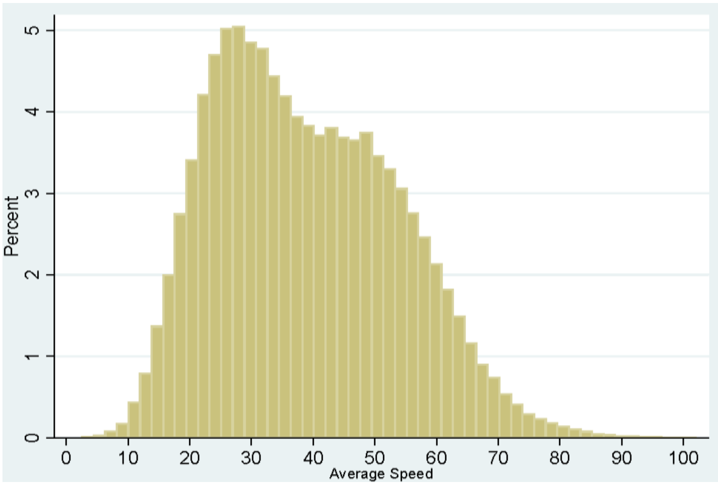
Since the magnitudes of the coefficients presented in the above table are marginal, their effect in terms of trip cost may seem infinitesimal. For example, the impact of a snowing on the day of the trip on ECR is only about 1.3 watts. However, it should be noted that the effects presented in the table are for each kilo meter driven, and thus, it could be a large effect when we consider, for example, on yearly travel distance bases.

Figure 11: The effect of Speed of Driving on Energy Consumption Rate of BEVs



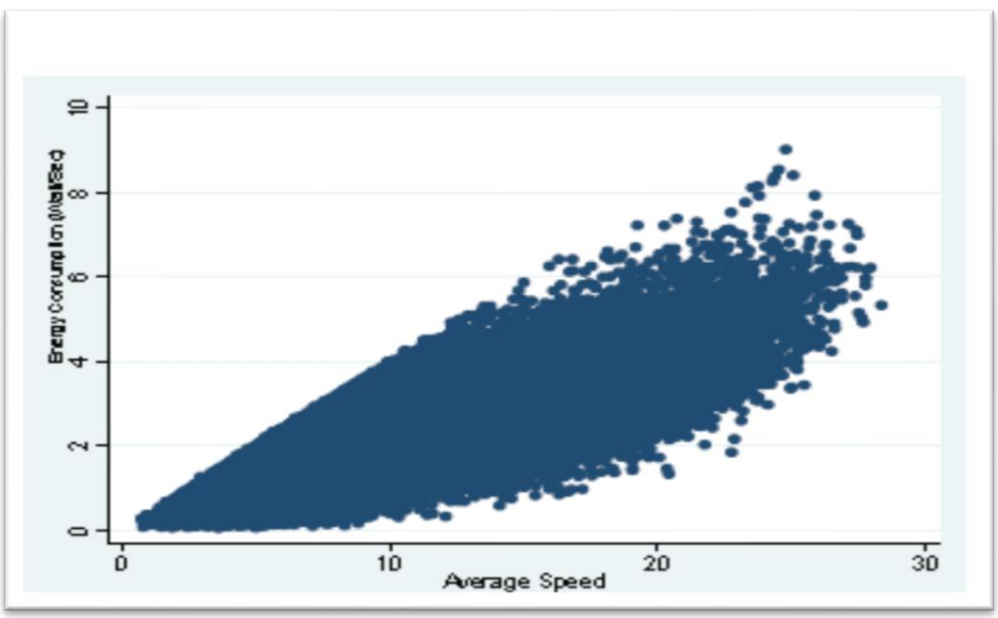
Note: A locally weighted scatterplot smoothing estimation (lowess) of the effect of speed of driving on ECR of BEVS, where on the horizontal axis is speed of driving (in km/h) and on the vertical axis is ECR (in wh/km). The fuel minimizing speed, found by running OLS following the shape of the lowess curve, is found to be 54 km/h (56 for winter and 50 for summer), which is lower than the optimal speed for conventional vehicles, about 65 km/h, found by El-Shawarby et al. (2005)

Figure 12: Observed Speed of Driving



Note: A large share of trips were driven at a less than enrgy saving speed of driving predicted in our model. This could be because BEVs were used for short trips as shown before in Figure 5, for which we expect low speed of driving.

Figure 13: The effect of Speed of Driving on Energy Consumption per unit of time (watt/second)



Note: the scatter plot shows positive the relationship between speed of driving (horizontal axis) and energy consumption rate per time (watt/second). Similar result is observed for convention cars fuel economy (Wang et al., 2008).

4. Conclusion

Analysis of the energy consumption rate and the corresponding range of battery electric cars under a given driving environment using real-world data is crucial for the costumers (to know the actual benefit of driving BEVs relative to other vehicles), for BEV manufacturers (to improve the overall efficiency of the car and to target different consumers living under different driving environments) and for the governments (to make social welfare improving policies with regard to BEVs).

A study about the energy consumption rate and the corresponding range of BEV as well as about the factors that affect energy consumption rate using real-world data that takes the drivers' characteristics, weather variations across years and over wider spatial area including urban and rural areas, and different road characteristics in to account is missing. The purpose of this paper is to fill this gap in general and in particular, to investigate the performance of BEVs under the Danish driving environment by analyzing a real-world data collected over the period of three years. We used GPS data collected by Clever A/s, Electric Mobility Operator in Denmark, that consisted more than a quarter of a million trips collected from about 741 BEV drivers collected over the period of three years as well as weather and road characteristic variables to find the ECR and the range three similar BEVs, namely, Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev, under the Danish driving environment. The data have detailed information about distance and energy consumption of each trip, driving patterns (speed and acceleration), trip date and time, geographical location and other variables.

We found that the mean energy consumption rate of the above mentioned BEVs is about 181 watt-hours per kilometer distance driven, which is higher than the 125 watt-hour per kilometer distance reported in the car specification. Similar, the mean range (assuming the 'car is to be driven until a fully charged battery is completely used) is about 94 kilometers, which is lower than the 130 kilometers range reported in the car specification. The observed difference, also found in the case of conventional vehicles, could be because the manufactures usually test BEVs from a long and continue driving until a fully charged battery becomes flat in that the energy used to overcome the inertia force to propel a parked car and the energy used to cool down a propelling car for each real-world short trips is saved in manufacturer testing.

We also found that there is high variation in ECR depending, among others, on driving patterns (speed and acceleration), weather variables, trip distance and road type (whether the trip on highway). Mean energy consumption rate is higher by about 34 % (225 wh/km versus 168 wh/km) and the range is lower by about 25 % (77 km versus 103 km) in winter than in summer. Using BEVs for relatively longer trips is better in terms of energy saving than using BEVs for short trips; we found about 20 % mean range difference between trips less than 2 kilometers and trips longer than 10 kilometers. Moreover, we found that speed of driving and temperature have non-linear effect on ECR, where too low or too high of both variables increases ECR. Energy consumption rate is low at about 14 degree centigrade temperature and speed of driving between 45 km/h to 56 km/h, ceteris paribus.

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