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ABSTRACT

This study analyses the driving range and investigates the factors affecting the energy consumption rate of fully-battery electric vehicles under real-world driving patterns accounting for weather condition, drivers' characteristics, and road characteristics. Four data sources are used: (i) up to six months driving pattern data collected from 741 drivers, (ii) drivers' characteristics; (iii) road characteristics; (iv) weather data. We found that the real-world driving range of BEVs is highly sensitive to driving pattern and weather variables. The most important determinants of energy efficiency found to be driving patterns (acceleration and speed, both non-linearly) followed by seasonal variation (a winter dummy), temperature (non-linearly) and precipitation. Mean ECR is higher by about 34 % and the driving range is lower by about 25 % in winter than in summer. A fixed-effects econometrics model used in this paper predicts that the energy saving speed of driving is between 45 and 56 km/h. In addition to the contribution to the literature about energy efficiency of electric vehicles, the findings from this study enlightens consumers to choose appropriate cars that suit their travel demand under the driving environment they live in, to know about energy saving patterns of drive, and to reduce driving range anxiety problem.

Keywords: fully battery electric vehicles, energy consumption rate, driving range, driving environment

1. INTRODUCTION

As the transport sector is one of the largest contributors of greenhouse gas at a global level (see, e.g., Alessandrini et al., 2012; Zahabi et al., 2014), there have been efforts by car-makers, car drivers and governments to improve fuel consumption efficiency, to reduce pollution and to limit dependence on fossil fuel. For example, some of the EU and US governments have set standards that limit the pollution level of cars and they use incentives and taxes to induce car manufacturers to produce, and car users to use fuel-efficient vehicles (Kono et al., 2008). Battery electric vehicles (BEVs) 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 BEVs can be obtained from renewable resources such as wind, solar power and hydro.

However, the market penetration rate of BEVs is lethargic, mainly because of high purchase prices, limited recharging infrastructures, limited driving range coupled with long recharging times, uncertainties concerning driving range and battery life, and risk aversion behavior in adopting new technologies (see, e.g., Egbue and Long, 2012; Birrell et al., 2014; Kihm and Trommer, 2014). It is clear that uncertainty plays a significant role in the (non-)choice of BEVs, especially when thinking about the cost and time for refueling a BEV with respect to a conventional vehicle. Uncertainty plays an even larger role when factoring in that customers have limited knowledge about the performances of BEVs and their sensitivity to driving environments, adversely affecting the demand for BEV (Jensen et al., 2013; Birrell et al., 2014). Accordingly, providing insight into the factors that affect the energy consumption rate (ECR) and driving range of BEVs under different driving environments is very relevant to support, on the one hand, consumers in choosing appropriate vehicles that suit their needs, and, on the other hand, manufacturers in distinguishing and targeting different customers depending on the driving environments that the customers live and move in.

Insights into the factors that affect the ECR and information about the driving range of conventional vehicles have been provided extensively, as the fuel consumption of conventional cars is well-documented in both the theoretical literature (Nam and Giannelli, 2005; Mellios et al., 2011) and the empirical literature (Ericsson, 2001; Brundell-Freij and Ericsson, 2005; Hu et al., 2012). Existing studies show that the fuel consumption rate of conventional vehicles is affected by road width (Brundell-Freij and Ericsson, 2005; Yao et al., 2007; Kono et al., 2008; Hu et al., 2012), road grade (Nam and Giannelli, 2005; Wang et al., 2008), traffic congestion and speed limits (Brundell-Freij and Ericsson, 2005), as well as by traffic information provided to drivers (Kono et al., 2008; Fotouhi et al., 2014). Existing studies also illustrate that driving patterns (in terms of speed and acceleration profiles) are the main factors affecting fuel consumption of conventional vehicles (Ericsson, 2001; El-Shawarby et al., 2005; Nesamani and Subramanian, 2006; Wang et al., 2008; Heide and Mohazzabi, 2013). Moreover, a number of studies have provided mathematical and technical detailed accounts of the effects of different car characteristics on the fuel consumption of conventional cars (see, e.g., Brundell-Freij and Ericsson, 2005; Nam and Giannelli, 2005; Heide and Mohazzabi, 2013; U.S.E.P.A., 2014). It should be noted that the effects of car features on fuel consumption are usually taken into account during the design of the vehicle by the manufacturers, and are usually made available to the consumers during the purchase of the vehicle (Kono et al., 2008; Ben-Chaim et al., 2013).

Insights into the factors that affect the ECR of hybrid electric vehicles (HEVs) using both fuel and rechargeable batteries have been provided to a lesser extent. For example, winter has been related to a decrease of 20% in the fuel efficiency of HEVs, and the overall fuel economy of HEVs with respect to conventional vehicles has been evaluated as possibly overweighed by the poor performance of HEVS in cold weather locations (Zahabi et al., 2014). The temperature has been found as relevant in other studies that have focused also on the driving environment (Fontaras et al., 2008; Alvarez and Weilenmann, 2012; Lohse-Busch et al., 2013), while the power ratio of HEV components and the applied control strategy have been demonstrated analytically related to the ECR of HEVs (Banjac et al., 2009).

Insights into the factors that influence the ECR of BEVs have been scarce, mainly because of their recent market penetration. Most studies include technical analyses that investigated the effects of car components on the ECR (see, e.g., Duke et al., 2009) and analyses by car manufacturers and other stakeholders. Large differences are usually observed between the results of car manufacturers and the results observed in real-world (Huo et al., 2011), mainly because manufacturers test BEVs by performing a long and continue test drive from a fully charged battery to a completely flat battery, thus, ignoring basic real-world energy expenditures such as 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 short trips. A limited number of studies have focused on the ECR and the driving range of BEVs: ECR of BEVs was estimated by taking into account driving patterns and car features from GPS data, and in-city driving was deemed more energy efficient than freeway driving (Wu et al., 2015); ECR of BEVs was compared by considering the driving range reported by the manufacturer versus the actual driving range of drivers (Birrell et al., 2014). However, these studies present limitations: (i) the study samples consisted respectively of one (Wu et al., 2015) and 11 drivers (Birrell et al., 2014), with obvious consequences on the possibility of generalizing any finding; (ii) the data collections did not cover the winter months, with obvious consequences on the possibility of analyzing the ECR in cold temperatures; (iii) the data analyses did not control for possible confounders, with obvious consequences on the possibility of assessing whether the differences were caused by other factors.

As aforementioned, the uncertainty and the consequent anxiety about the driving range and the ECR of BEVs is one of the major barriers to their wider market penetration. It is therefore essential to provide insights into the actual ECR and driving range of BEVs under different driving environments as well as the factors that affect them while controlling for drivers' characteristics, weather variations, spatial areas, and road characteristics. The current study fills this gap by analyzing real-world data collected over a two-year period in Denmark, namely by addressing questions about the ECR of BEVs under various driving environments, the sensitivity of BEVs to speed and acceleration profiles, the optimal speed for the most energy efficient use of BEVs, the variability in the performances of BEVs with varying factors such as speed, wind, temperature, and location. Addressing these questions not only could help customers in reducing the uncertainty about energy consumption and driving range because of the provided information, but also could support customers in adopting the optimal driving pattern for energy efficient driving.

Big data are used for providing answers to these questions, as more than a quarter of a million trips performed by 741 BEV drivers have been analyzed in the current study. The data were collected over a two-year period between January 2012 and January 2014 by Clever A/S, an electric mobility operator in Denmark, using three models of BEVs, namely Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev. The data contained information for each trip about vehicle positioning (i.e., longitude, latitude), driving patterns (i.e., speed profile, acceleration profile), battery charge level, time and duration of the trip, and road characteristics after map-matching. Data included also information about the weather conditions during each trip as well as the driver characteristics as reported by drivers while renting the BEV. The analysis focused on the computation of the ECR and the corresponding driving range of BEVs from the large sample of trips in real-world driving conditions, and the estimation of the effects of driving patterns, road characteristics and weather conditions on the ECR of BEVs from the estimation of individual-specific fixed effects econometric models. Moreover, the analysis proposes a simple formula that allows consumers to compare BEVs and conventional vehicles in terms of fuel (electricity) cost under varying intensity of the winter season. The current study contributes to the literature about energy efficiency of BEVs by overcoming limitations of existing studies: (i) the sample of the study is significantly larger than previous studies with about 2.3 million km driven; (ii) the seasonal variation is accounted for, as the study period covers two summers and three winters; (iii) the weather effects are considered, as the study looks at the effect of temperature, precipitation and wind speed; (iv) the actual driving patterns are analyzed, as the speed and acceleration profiles are collected for each trip; (v) econometric models are used to disentangle the effect of each variable on the ECR after controlling for possible confounders.

The remainder of this paper is structured as follows. The next section presents the data collection and the methods used to compute the ECR of BEVs and to estimate the model of the ECR of BEVs. Then, the results of the computation and the estimation are presented, and conclusions and further research directions are offered in the last section.

2. METHODS

2.1 **Data Collection**

Four data sources were used for this paper: (i) driving patterns collected from GPS data loggers installed on 200 BEVs used by 741 drivers for 276,102 trips and about 2.3 million km travelled; (ii) drivers' characteristics obtained from registration during receiving BEVs for 3 to 6 months drive; (iii) road characteristics collected from the map-matching of the GPS data with the Danish road network; (iv) weather information obtained from the Danish Meteorological Institute (DMI).

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" (in English: "test an electric car") where Danish drivers were invited to drive BEVs and were proposed an agreement to collect information about their trips during the period. The total number of individuals participated in the project was 1600, but the number of drivers with relevant data for this paper is 741. Each driver had been using a BEV for 3 to 6 months, after which, the BEV was given to other drivers in that 1600 drivers used the 200 BEVs within two years. The data were collected using GPS during the period from January 2012 to January 2014, and the GPS data loggers were mounted on three fully BEV models, namely Citroen C-Zero, Peugeot Ion, and Mitsubishi iMievst, which are made by the same manufacturer and are practically identical.

Variables related to driving patterns (i.e., speed profiles, acceleration profiles), date and time of each trip, distance and duration of each trip, geographical coordinates of each trip, and percentage change in the battery charge level for each trip, were extracted from the GPS data. Time-of-day periods and seasonal variation were defined on the basis of the date and time stamps of the GPS loggers.

Variables related to income and demographic characteristics (age and gender) of drivers were collected during the registration process for testing BEVs. The drivers were mainly men (56%), with average age of about 44 years old, and heterogeneous distribution of income as 48% declared a yearly income higher than the then mean national income.

Controlling for the road and traffic characteristics revealed cumbersome since road grade and traffic congestion dynamics even within a trip. However, after map-matching the GPS data for each trip, it was considered that road grade is not relevant to Denmark as one of the flattest countries in the world, and we use rush hour as a proxy to traffic congestion hours. Moreover, it was discerned whether each trip was performed on a highway in order to account for road variability.

Controlling for the weather conditions revealed also cumbersome because weather varies dynamically across time and location even for a single trip. It was considered that a driver could experience different types and level of weather conditions, but the changes would have marginal effects when considering that most trips in Denmark are rather short. Accordingly, and similarly to existing literature, we the mean values for temperature, precipitation, wind speed and visibility of each trip as reported by DMI.

Considering the initially registered 276,102 trips, the data cleaning process implied looking for missing values and possible errors in the variables. In particular, 10,977 trips had missing information about the battery charge level, 10,420 trips had unreliable information with extremely low or high values of battery charge level variation, and 9,394 trips had missing information concerning the identity of the driver. Following the data cleaning process, the data analysis focused on 239,247 trips for the descriptive part and 229,853 trips for the regression part.

2.2 Data Analysis

2.2.1 Descriptive Analysis of BEV Performance

Initially, this study examined the performance of BEVs in terms of ECR (analogous to the fuel consumption rate for conventional cars). Namely, the ECR was calculated as the ratio between the power consumed and the distance traveled for different models and different driving environments:

$$\text{ECR} = \frac{\text{Power consumed (kWh)}}{\text{Distance traveled (km)}} \qquad (1)$$

The lower is the ECR, the better is the energy efficiency. In this study, the data contained the percentage change in battery charge level before and after each trip, which implied that the value obtained from the data collection had to be multiplied by the watt-hour of the battery of the vehicle (i.e., 16 kWh) in order to obtain the power consumed in kWh.

Given the ECR, the driving range of BEVs was computed as follows:

$$\text{Driving Range} = \frac{\text{Power of a fully charged BEV (kWh)}}{\text{ECR (kWh/km)}} \qquad (2)$$

It should be noted that the driving range depends on the battery capacity, the car performance, or both. Accordingly, a higher driving range would not necessarily indicate that the BEV performs better in terms of ECR, but could possibly relate to a higher battery capacity that comes at a heftier price. For this reason, comparing ECR between BEVs provides more correct insight into the energy efficiency of BEVs.

2.2.2 Modeling Analysis of the ECR Of BEVs

Explaining the factors that affect the ECR of BEVs under different driving environments is relevant to consumers for choosing vehicles that suit their driving needs and to manufacturers to distinguish and target market segments according to their driving environments. Accordingly, this study provides the estimation of a model that unravels the sign and magnitude of the factors that affect the ECR.

An unobserved effects model was used because this is the most suitable model for panel data as the ones collected in this study (Wooldridge, 2000). In fact, considering unobserved (latent) individual-specific effects allows controlling for unobservable factors such as car maintenance (e.g., oil, brakes), weight load, and usage of car devices that could affect energy consumption, which are less likely to vary for an individual while they certainly vary across individuals. Accordingly, an unobserved individual specific effect model was estimated to explain the ECR variation. A general model that can be used to estimate the factors explaining the variation in ECR can be given by

$$ECR_{it} = \theta_t + X_i\beta + W_{it}\alpha + Y_{it}\delta + Z_{it}\gamma + \phi_i + \upsilon_{it} \quad (3)$$

where ECR_{it} is the ECR of a trip *by* driver *i at time t*, θ denotes a time-varying intercept, X_i is a row vector of the characteristics of the vehicle used by individual *i*, W_{it} is a row vector of weather variables that vary among individuals *i and* across time *for an individual*, Y_{it} is a row vector of road characteristics that vary across individuals *i and* across time *t*, Z_{it} is a row vector of household characteristics that could vary across individuals *i* and within a household across time t, ϕ_i is individual-specific unobserved effect that is time-invariant, υ_{it} is the idiosyncratic error term with mean zero and is uncorrelated with any of the explanatory variables, and the column vectors α, β, γ and δ contain the population parameters to be estimated.

The choice of the appropriate model among unobserved effects models mainly depends on how the ϕ_i is correlated with the explanatory variables. The random effects model is preferred to fixed effects model when ϕ_i is uncorrelated with explanatory variables, and when the main variables of interest are dummies. Whereas the fixed effects model is preferred when there is strong correlation between the unobserved factors and the explanatory variables included in the model since the unobserved time-invariant variable will be effectively concealed out by time-demeaning in the fixed effects model. One way of choosing between random and fixed effects models is to conduct the Hausman test (Wooldridge, 2010). Having found that the fixed effects model is preferred to random effects model via a Hausman test for the data collected in this study, a fixed effects model was estimated to investigate the factors that explain the variation of *ECR.* Correspondingly, the explanatory variables X_i, and Z_{it} and the latent variable, ϕ_i, were canceled out by time-demeaning given that these variables did not vary over the period in which the data were collected. Accordingly, the model we estimated is given by

$$ECR_{it} - \overline{ECR}_i = \theta_t - \bar{\theta} + \left(W_{it} - \bar{W}_i\right)\tilde{\alpha} + \left(Y_{it} - \bar{Y}_i\right)\tilde{\delta} + v_{it} - \bar{v}_i \quad (3')$$

Where the bars subtracted on each corresponding variable denotes the mean of each variable computed over time, not the mean across individuals. That is, for example, $\overline{ECR}_i = \frac{1}{T}\sum_t ECR_{it}$, $\bar{W}_i = \frac{1}{T}\sum_t W_{it}$, and so on. This transformation enables to cancel out the latent variable that could affect the estimation result otherwise, and the model provides consistent estimates regardless of the correlation between the latent variable and the explanatory variables (Wooldridge, 2010). The fixed effects model enables to control for unobserved activities of drivers corresponding to driving BEVs, such as weight loaded, usage of the car tools, etc. that could bias estimates.

3. RESULTS

In this section, the results from the data analyses are presented. The main results presented in this section include descriptive statistics results about the trips, ECR (by different categories), and result from the fixed effects model estimation of the factors explaining ECR variation.

3.1 OVERVIEW of TRIPS by BEVS

On average, each driver had 307.1 trips during 90.7 days where the individuals used BEVs. Concerning the length of the trips, about 50% of trips were less than 5 km, and only about 1 % of the total trips were over 50 km. A possible reason for the short trip distances could be the fact that about 39% of Danes commuted less than 5 km in 2013 (Denmark Statistics, 2014), and another reason could be that the customers had a range anxiety problem and used the BEV for shorter distances.

Given the average short distances, it is not surprising that a great share of individuals did not recharge the BEVs upon arrival from each trip. It is however interesting that the infrequent recharging does not correspond to waiting for having an empty battery: the mean and the median of battery charge when the recharging was performed were equal respectively to 55.5% and 56%, namely individuals recharged their BEVs well before risking to have their batteries empty.

3.2 Observed ECR of BEVs

3.2.1 Overall ECR

The mean ECR in the sample equals 0.183 kWh/km, namely each km traveled consumes on average 183 Wh (= 0.183 kWh) and hence a minimum power of 9.125 KWh must be available for a trip of 50 km not requiring recharging of the battery.

Figure 1 presents the distribution of the ECR from the 239,247 trips in the analyzed data. The vertical line at 125 Wh/km denotes the mean ECR from the specification of the BEVs in the sample, whereas the vertical line at 183 Wh/km denotes the mean ECR from the observation of the data. The resulting driving range is about 25.5% lower than the driving range reported in the specification of the BEV models used in this study. Figure 1 shows that the distribution of the ECR presents high heterogeneity and indicates that BEVs consume more energy per distance unit than reported by manufacturers since a massive share is clearly over the specification of the BEVs used in the study. A reason for the difference is that the testing conditions of manufacturers do not include the energy consumed to propel a parked vehicle or to cool down a propelling vehicle that characterize real-world trips. Another reason for the difference and for the heterogeneity is possibly the difference in driving environment whose investigation motivated the modeling of the variation of the ECR presented later.

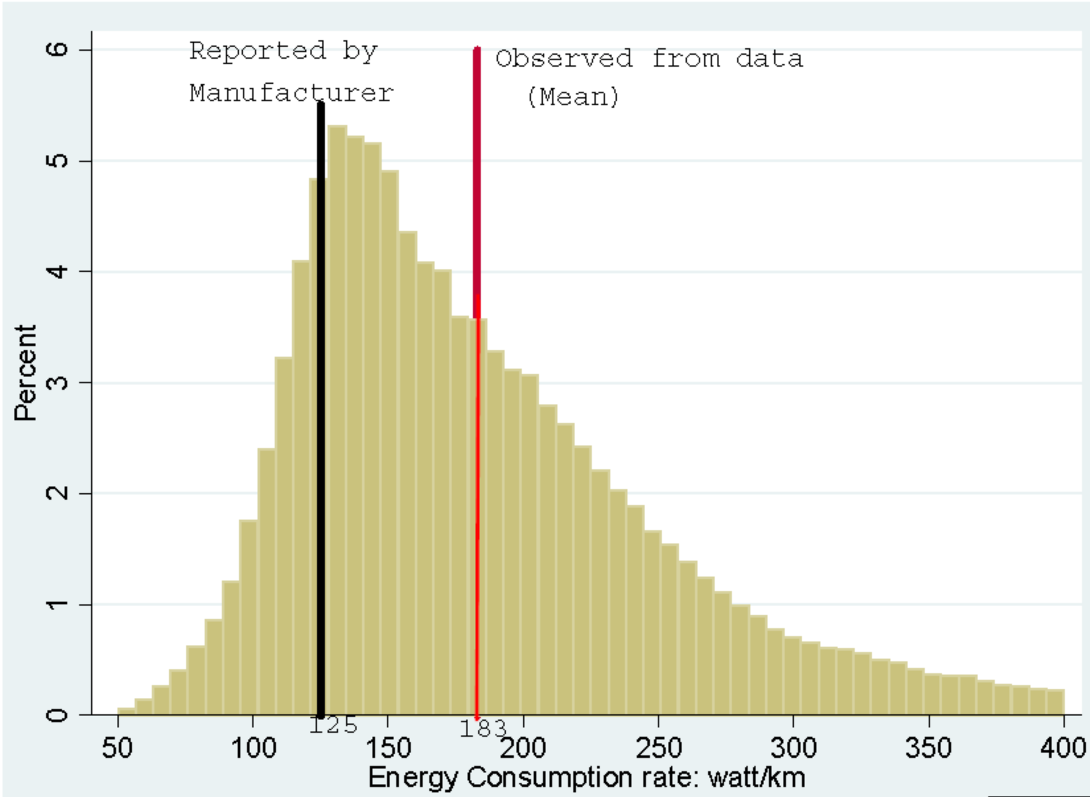

Figure 1 The distribution of ECR, and observed versus reported ECR of BEVs

3.2.2 ECR by Season

The ECR was computed for the summer and the winter seasons, and results showed that ECR is higher and consequently the driving range is shorter in winter with respect to summer: the average ECR is equal to 0.168 kWh/km during the summer and 0.225 kWh/km during winter, with an observed 34% increase in consumption in winter per km driven. Both a parametric t-test and a non-parametric Mann-Whitney test proved the difference to be statistically significant, and the difference is higher than the 20% reported in Canada for hybrid vehicles (Zahabi et al., 2014).

3.2.3 ECR by Trip Distance

As driving patterns could vary with the trip distance (Fosgerau, 2005), and in turn the distance could affect the ECR (Ericsson, 2001), it is relevant to consider the ECR for different trip distances in order to know for which trip distances BEVs are more energy efficient. The distribution of the distances in the trips analyzed in this study suggested to consider short trips (less than 2 km), medium trips (between 2 and 10 km) and long trips (longer than 10 km).

It emerges that the mean ECR decreases (and consequently the mean driving range increases) with the increase of the trip distance: for example, in average short trips consume 40 Wh/km more than medium trips and 57 Wh/km more than long trips. The difference is observed for all percentiles except the lower one, and it is statistically significant according to both a parametric t-test and a non-parametric Mann-Whitney test. Roughly speaking, these findings suggest that BEVs are more energy-efficient for individuals with relatively longer commuting distance rather than ones with shorter commuting distance.

3.2.4 ECR by Road Type

As road characteristics have an effect on the fuel economy of conventional and hybrid vehicles (Brundell-Freij and Ericsson, 2005; Ericsson, 2001; Zahabi et al., 2014), ECR was computed for highway and non-highway trips.

No clear difference emerges between driving on highway or non-highway roads, although the average ECR is slightly lower for highway portions of the trips. More specifically, while the 5th and 25th percentiles of the ECR of trips on highway are higher (and consequently the driving ranges are shorter) than for trips on non-highways, the opposite is observed when looking at the mean, median, 75th and 95th percentile of the ECR of BEVs. The differences are not statistically significant according to both a parametric t-test and a non-parametric Mann-Whitney test.

3.3 Comparison of BEVs and Conventional Vehicles in terms of Energy Cost

Having the mean ECR from the analyzed data allows formulating an equation for the (rough) comparison of BEVs and conventional vehicles in terms of fuel efficiency, at least in the Danish driving environments.

Consider that the mean ECR of BEVs in the analyzed sample is equal to 0.183 kWh/km, and that the electricity tariff that the individuals pay for recharging their BEVs is equal to P_e per KWh. Accordingly, the mean electricity cost per km traveled is equal to 0.183 P_e. Consider that the mean fuel consumption per km traveled of a conventional car is equal to v, and that the fuel tariff that the individuals pay for fueling the car is equal to P_f per liter. Obviously, driving a BEV is cheaper than driving a conventional vehicle in the case that the cost per km of the former (0.183 P_e) is lower than the cost per km of the latter (vP_f), namely if:

$$0.183P_e \leq vP_f \tag{4}$$

For example, if the fuel cost P_f is equal to 11 DKK/liter (i.e., current price of gasoline in Denmark) and the fuel consumption v is equal to 0.05 liters (i.e., 20 km/liter), then it would be cheaper to drive a BEV if and only if the electricity tariff P_e is not higher than 3 DKK/kWh.

Consider a possible extension that differentiates the ECR into summer and winter seasons, and define the number of months θ with summer weather. Given the mean ECR for summer and winter computed from the analyzed data, it would be cheaper to drive a BEV rather than a conventional vehicle in terms of only running cost if and only if:

$$0.168P_e\left(\frac{\theta}{12}\right)+0.225P_e\left(\frac{1-\theta}{12}\right)\leq vP_f \tag{5}$$

It should be noted that more precision could be obtained by relating to the number of days rather than the number of months.

3.4 **Modeling of the ECR Variation**

Table 1 presents the estimation results of the unobserved individual specific fixed effects model that explains about 70% of the ECR variation between drivers, 28% of the ECR variation within drivers, and 41.5% of the ECR variation overall in the sample of 229,853 trips. Interestingly, most of the explanatory variables are statistically significant and have the expected sign also when considering non-linearity in their relation to the ECR. The model estimates present effects on the ECR per km traveled, which means that the potential effects when considering yearly travel distances are considerably high.

Speed of driving and acceleration are extremely relevant to the ECR variation. The seasonal variation is proved to be associated with the ECR, and this finding is important because it shows that winter is positively related to an increase in ECR even when controlling for other variables. The weather conditions are also very important in explaining the ECR variation. It should be noted that the lower the ECR is, the better is the fuel efficiency, and thus statistically significant negative parameters in this specific model indicate which variables have a positive effect in terms of energy efficiency and driving range.

TABLE 1 ECR Model Estimates

Explanatory Variables	Estimate	standard error	p-value
Mean driving speed	-19.000	0.365	0.0000
Mean driving speed square	0.761	0.015	0.0000
Mean acceleration	55.521	7.156	0.0000
Mean acceleration square	27.828	9.150	0.0020
Trip distance	-1.110	0.062	0.0000
Trip distance square	0.010	0.001	0.0000
Winter	14.687	0.364	0.0000
Highway	0.534	0.381	0.1610
Rush hour	-1.926	0.204	0.0000
Battery level (at trip start)	3.401	0.206	0.0000
Battery level (at trip start) square	-0.056	0.003	0.0000
Battery level (at trip start) cube	0.000	0.000	0.0000
Temperature	-4.807	0.040	0.0000
Temperature square	0.081	0.002	0.0000
Wind speed	0.695	0.042	0.0000
Visibility	-0.118	0.005	0.0000
Precipitation	5.287	0.229	0.0000
Constant	135.489	6.378	0.0000
R-square: within	0.2714	sigma_u	20.0258
R-square: between	0.7020	sigma_e	44.8110
R-square: overall	0.4078	rho	0.1665
Number of observations			229,853

An interesting finding from the model estimation is that the mean driving speed presents a quadratic term, namely driving at both very slow and very fast speed increases the ECR (and, correspondingly, decreases driving range). A possible explanation for the slow speed relation could be associated with the energy required for keeping the BEV moving for a longer period, while a possible reason for the high speed relation could be linked to the energy required to speed up the BEV. To substantiate this finding, we also run a locally weighted scatter plot smoothing estimation of the effect of speed of driving on ECR.

Another interesting finding from the model estimation is the fact that the acceleration has an important effect on the ECR variation, and that this variation is positive for each unit increase in the acceleration, ceteris paribus. This finding is in line with another study looking at acceleration effect on the fuel consumption rate of conventional and hybrid vehicles (Zahabi et al., 2014), but there is a clear quadratic effect that has been ignored in previous studies.

The seasonal variation has a significant impact on the ECR, with a higher consumption of 15 Wh/km in winter with respect to summer, even when controlling for the weather effects such as temperature, precipitation, and wind. It is possible to assess the total effect of the winter season by taking the average values of the weather variables in the winter months and calculate the compound effect on the ECR, which suggests that the 15 Wh/km are a conservative estimate.

Another interesting result from the model estimation is that the temperature has a non-linear U-shaped effect on the ECR, namely driving at both too low and too high temperature affects (negatively) the energy efficiency of BEVs. This finding is not in line with the results reported by Birrell et al. (2014) that did not find any relation between temperature and driving range of BEVs, possibly because there was not enough variation in the temperature for a study conducted between May and October. This finding is in line with the results presented by Lohse-Busch et al. (2013) that observed an increase of about 100% in the ECR of BEVs in a controlled laboratory experiment with temperature falling from 70 °F to 20 °F. It should be noted that previous studies did not consider non-linearity that appears intuitively relevant, as lower temperatures require more energy for warming the vehicle, and higher temperatures need more energy for cooling the vehicle. Ceteris paribus, the mode indicates that the most favorable temperature in terms of energy efficiency of BEVs is equal to 14 °C.

Moreover, it is very interesting that the initial level of the battery has a polynomial (third degree) effect on the ECR. Specifically, individuals can observe different rates of battery power consumption for driving in the same environment for the same distance, just because of a different battery charge level at the beginning of the trip.

Table 1 reveals also that, as expected, wind speed and precipitation have positive and statistically significant effect on ECR, whereas visibility (sunshiness) has a positive and statistically significant effect on ECR. Driving on highway does not seem to have a statistically significant (within conventional levels of significance) effect on ECR. This may not be surprising since the main differences between driving on and off highway, speed of driving and acceleration, are already controlled for.

4. CONCLUSIONS

The current study proposes the analysis of the ECR and the factors that affect its variation by harnessing big data from a variety of sources. The study is innovative in its investigation of a very large number of vehicles, an immense number of trips (over 230,000) and km travelled (about 2.3 million), and a great number of sources of information concerning vehicles, roads, weather and seasons. Moreover, the study is novel in its proposition of a model for disentangling the effects of different variables on the ECR of BEVs.

The findings from this study provide insight into the actual energy efficiency of BEVs. The overall mean ECR is equal to 0.183 KWh/km, which for a traditional battery capacity of 16 KWh of a Citroen C-Zero corresponds to a mean driving range of about 87 km, far less than the driving range of 130 km reported by the manufacturer or even 150 km set at the European Driving Test. The consumption of electricity is significantly higher in winter, as the ECR increases by about 34% with respect to summer conditions, which for countries with longer (shorter) winters implies a lower (higher) driving range. Most relevantly, the findings from the calculation of the ECR allow understanding where the price of electricity should be for consumers to have convenience from an energy cost perspective of purchasing a BEV rather than a conventional vehicle.

The most significant findings from this study provide insight into the effect of several variables on the ECR variation. Remarkably, several variables have quadratic or polynomial effects. This appears logical for example for temperature, given that more energy needs to be spent to warm the vehicle at lower temperatures and to cool it down at higher temperatures, and for speed, given that more energy requires to be spent to move the vehicle from lower speeds and to maintain higher driving regimes. Optimal values for the temperature at 14 °C and for the driving speed at about 52 km/h are found from the model estimation results, and these are on the one hand good indicative values for potential consumers of BEVs who might want to maximize the use of their battery and hence their vehicle. Interestingly, the battery charge level at the beginning of the trip has a polynomial effect that indicates how the battery level decreases drastically for full charge rather than for lower charge levels, and these are on the other hand not so good indicative values for potential customers of BEVs who might want not to take chances given anxiety about the performance of the vehicles.

The results from this study could be used in order to perform a cost-benefit analysis of the introduction of BEVs under different market penetration scenarios, to estimate more accurately the level of emissions of BEVs in comparison with conventional vehicles (while accounting the emissions related to the charging), and to predict more precisely the driving range of BEVs that causes the anxiety hindering most consumers to prefer BEVs over conventional vehicles. Specifically, the results indicate that optimal driving speed and acceleration within given weather conditions can be selected by consumers in order to have energy efficient vehicles guaranteeing to reach the destination without the need for recharging.

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