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# A latent-based segmentation framework for the investigation of charging behaviour of electric vehicle users☆

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ABSTRACT

Electrification of transport is deemed by many countries worldwide as one of the key strategies to mitigate $CO_2$ emissions, yet the availability of reliable public charging infrastructure systems represents a potential serious bottleneck to such endeavours. Existing studies exploring battery electric vehicle (BEV) charging behaviour are typically based on either non-representative samples or stated choices experiments. This paper analyses observational data from a representative sample of German BEV owners who provided information on mileage and charging activities over a timeframe of eight weeks. BEV charging patterns, related vehicles kilometres travelled (VKT) and battery charging behaviour are assessed via a multifaceted empirical framework that pairs a hazard survival-based model with a log linear regression approach. A latent class method is also employed to segment BEV owners into different charging segments. The model suggests two types of charging behaviour exist, consisting of regular and irregular chargers. Charging frequencies and patterns are found to be radically different between the two groups under study, with regular chargers estimated to charge their vehicles 1.5 times more than irregular chargers. Lastly, the framework proposed is used to explore how charging behaviour will mutate due to both technology advancements (BEV driving range improvements) and user-centric factors (VKT variations). Neither technological or user factors are predicted to substantially affect the inter-charging duration of irregular chargers, whereas both increasing BEV driving ranges and reducing VKT results in a longer elapsed time between two consecutive charges for regular chargers.

## 1. Introduction

Given that the transport industry is responsible for approximately one third of global $CO_2$ emissions (International Energy Agency (IEA), 2022), electrification of the transportation sector represents a key strategy for combating climate change (IEA, 2016). Understanding the charging behaviour of electric vehicle (EV) owners is therefore crucial for both transport planners as well as those working in the energy sector. To date, numerous decarbonization strategies have been introduced worldwide to increase the uptake of EVs, including policies that restrict the ability of owners to drive or purchasing conventional vehicles (Chi et al., 2021; Liu et al., 2021;

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Ma et al., 2020; Zheng et al., 2022; Pellegrini et al., 2023a), or incentivise the acquisition of more fuel-efficient vehicles (Hardman et al., 2017; Pellegrini et al., 2023b; Pellegrini and Rose, 2023), such as allowing EVs access to high-occupancy vehicle (HOV) lanes (Jenn et al., 2018) or the deployment of dedicated parking spots for electric automobiles (Gong et al., 2020), among others. Other policies have focused on reducing charging costs through subsidising electricity costs (e.g., Greaker, 2021; Kim et al., 2022), improving public charging infrastructure (e.g., (Li and Ouyang, 2011; Yang et al., 2020), or via the introduction of national vehicle standards (e.g., Das et al., 2020).

Although various structural reforms adopted by national governments have contributed to accelerating the transition to cleaner transport alternatives, there remains a significant segment of the public who are hesitant to purchase EVs, in part due to the (perceived) unreliable nature of the public charging infrastructure networks (McNutt and Rodgers, 2004; Graham-Rowe et al., 2012; Kim et al., 2017; Wollbertus et al., 2018; Greene et al., 2020). The lack of sufficient public charging infrastructure can in a large part be attributed to the reluctance of various stakeholders to invest in the development of a robust public charging network due to perceptions about the unprofitability of the EV market (Gnann and Plötz, 2015; Melaina et al., 2017).

Despite much of the public discourse relating to public charging of EVs, it is worth noting that most of charging activities are currently undertaken at home. Indeed, evidence suggests that approximately nine out of ten charging events occur at private dwellings in continental Europe (Franke and Krems, 2013a; IEA, 2020), with 70 percent of charging in the UK, United States and Canada (Neaimeh et al., 2017; Funke et al., 2019). Unfortunately, the ability to charge an EV at a person's place of residence is not uniform across the population, with accessibility of EV private charging infrastructure (e.g., Level 1 or Level 2[1]) subject to the availability of off-street parking, as well as dependent on the type of dwelling the EV is housed at (e.g., individual houses vs condominiums) (LaMonaca and Ryan, 2022; Alexander, 2022; Zhongying, 2023). Recently, Pellegrini et al. (2023b) evaluated the intention of Australian households to install EV home chargers by analysing data extracted from a discrete choice experiment (DCE) administrated to residents of either separate private dwellings or town houses/apartments belonging to building complex. The authors conclude that both sampled populations are keen to upgrade the infrastructure to permit the home charging of EVs, with apartment residents holding strong positive preferences towards chargers located at privately allocated parking spaces relative to communal bays. A promising alternative to the scarcity of EV charging infrastructure may lie with the development of EVs with photovoltaic solar panels that will allow for improvements in the driving range capacity of such vehicles (Masuda et al., 2017; Girard et al., 2019). For example, Ghasri et al. (2021) quantify that Australian consumers are on average inclined to pay a premium of approximately AU$18.13 for every added driving range kilometre originated from solar photovoltaic technology.

The aim of this study is to contribute to the literature on charging behaviour of EV owners by analysing the real-world data of 2,898 charging events associated with 154 EVs obtained from the German Mobility Panel (MOP) (https://mobilitaetspanel.ifv.kit.edu). The MOP is one of the most comprehensive observational data sets currently available, as well as being based on a nationally representative sample, with the latest wave being collected in Spring 2022 at the time of this study (see section 3 for additional details). We propose the use of a latent based methodological framework that couples a heterogeneous hazard-based (henceforth, H-HD) model (Bhat et al., 2004; Bhat et al., 2005) with an heterogenous vehicle kilometres travelled (henceforth, H-VKT) regression model (Yamamoto et al., 2018; Hasan and Simsekoglu, 2020). Whilst the H-HD is used to assess what determinants influence the frequency of EV charging, the H-VKT is employed to capture nuances pertaining to EV usage between consecutive charging episodes. The two proposed models are analytically linked via the inclusion of the battery usage (BU) before charging, calculated as the predicted VKT divided by the vehicle driving range according to the car maker, into the H-HD. By doing so, we are able to directly measure how the battery usage impacts on the inter-charging duration (see, for example, Daina and Polak, 2016) without incurring any potential endogeneity issues that might arise with the incorporation of the VKT into the list of explanatory variables for the H-HD model. Further, EV owners are profiled into different segments, these being either irregular or regular chargers depending on their charging regularity, since the two groups are likely to exhibit radically different behaviour. The assignment of individuals to the two identified groups is undertaken in a probabilistic manner, as there is no prior information as to what typology of user the EV driver is (see Kim et al., 2017).

The next section reviews the relevant literature in this research field, followed by Section 3 that outlines the econometric framework that stands at the core of this study. Section 4 describes the data that we employ for the empirical analysis whilst Section 5 presents the estimated findings obtained from the joint estimation of the H-HD and H-VKT models, alongside a discussion of the results that derive from two simulated exercises. Section 6 draws some police implications and provides concluding remarks.

## 2. Literature review

Whilst numerous studies have examined the impact of charging infrastructure changes on the shift to electromobility (e.g., Dong et al., 2014; Ghamami et al., 2016; Hardman et al., 2018; Funke et al., 2019; Globisch et al., 2019; Illmann and Kluge, 2020; Zhang et al., 2020; Schulz and Rode, 2022), the existing knowledge about charging habits of EV owners remains limited (Kim et al., 2017). At present, one of the major challenges faced by researchers relates to an insufficient amount of real-world data on EV charging patterns, often resulting in policy recommendations grounded on strong assumptions (e.g., driving behaviour of EVs is similar to that of traditional passenger vehicles), or empirical investigations involving relatively small sample sizes (Khan and Kockelman, 2012; Tamor et al., 2015; Jakobsson et al., 2016; Yang et al., 2016). For example, Zoepf et al. (2013) examine the charging events related to 125 plug-in hybrid electric vehicles (PHEVs) and found that electric cars are typically recharged after the final trip of the day when the

[1] The charging power of Level 1 is approximately between 1.4kW and 2.4kW, with a full recharge of the vehicle occurring anywhere from 8 to 40 h. Level 2 EV chargers, on the other hand, have a charging power of up to 7.2kW with a driving distance of about 29 km per hour of charge.

vehicle is located at home, and when there exists a gap of more than three hours from the next trip, although significant heterogeneity was found to exist within the sample. Franke and Krems (2013b) conclude from a six-month EV field study involving 79 EV owners that on average drivers travel 38 km per day and recharge their vehicles three times per week. Speidel and Bräunl (2013) analyse data from 11 EVs and 23 charging stations collected during the Western Australian Electric Vehicle Trail conducted between 2010 and 2012, finding that 83 percent of charging events occur when the battery of vehicles are at more than half charge. Khoo et al. (2014) make use of various statistical modelling techniques to examine charging occurrences of 33 EVs employed in the Victorian (Australia) EV Trail, reporting that sampled households recharge their EVs 0.54 times per day with negligible differences in charging frequencies being captured between weekdays and weekends.

Sun et al. (2015) evaluate normal charging (Level 1 and Level 2) episodes after the last trip of the day involving 483 EVs belonging to an EV usage trail conducted in Japan between February 2011 and January 2013. Their results suggest that the state of charge (SOC), charging intervals (in days) and vehicle-kilometres to be travelled on the next trip are three key predictors for the analysis of recharging choices. This research involved by far the largest empirical sample among those here reviewed, although experimental data were gathered over one decade ago. Daina and Polak (2016) examine the inter-charging duration of 20 EVs drawn from the Low Carbon London project and assert that the frequency of charging decreases by approximately six percent as the SOC before charging increases. From an Irish study on charge and trip making behaviour involving 72 EV users, Weldon et al. (2016) reveal that EVs are regularly charged independent of both the battery's state of charge before charging, and the distance travelled between consecutive charging activities. Finally, Kim et al. (2017) examine four-years of charging transactions data of public EV points in the Netherlands, finding that extreme weather conditions have the effect of delaying the next charge at public stations based on 449,844 charging events.

Other studies have examined charging behaviour patterns by analysing data obtained from DCEs. Whilst DCEs are immune to the typical limitations of observational studies, including the difficulty of collecting sufficiently large and representative samples, they tend to provide limited opportunities to develop behavioural models based on real-world scenarios. Examples of such studies include Wen et al. (2016), who design a DCE to elicit EV drivers' preferences towards different charging opportunities, noting that respondents are on average willing to pay an extra US\$2.35/hr for Level 2 charging and US\$7.85/hr for fast charging above the premium paid for Level 1 charging. Daina et al. (2017) utilize a random utility-based model to assess the interrelated stated decisions of activity-travel scheduling and charging choices, estimating significant heterogeneity across the 88 surveyed respondents with regards to charging cost, the battery charge state after charging, and the duration of the charging event. Latinopoulos et al. (2017) implement a risky-choice framework to study out-of- home stated charging preferences of 118 respondents under the assumption of parking and charging prices changing dynamically and articulate that interviewees might procrastinate with respect to undertaking charging activities in the expectation of obtaining a cheaper charging bundle.

The contribution of the current paper to the literature on charging behaviour is twofold. First, we jointly analyse vehicle usage and charging patterns of a representative sample of German BEV owners, as opposed to most observational studies being based on non-representative and outdated samples. Indeed, some of the abovementioned articles were published more than a decade ago when the technology was still in its infancy with EVs being primarily used by early adopters. Second, the present study represents one of the first attempts (if not, the first one) to assess charging behaviour of EV users via the formulation of an econometric framework that simultaneously captures the determinants influencing vehicle usage patterns and their impact on charging time intervals.

## 3. Methodology

This section illustrates the methodological approach that we utilize to investigate charging behaviour of EV owners. As mentioned above, the proposed approach pairs a H-HD model with a H-VKT regression model, with the former examining inter-charging duration (days) patterns whilst the latter evaluates the determinants affecting EV usage between successive charging instances. Given that the researcher cannot identify the type of EV user *a priori*, individuals are classified as either irregular or regular chargers through a latent-based segmentation method, which allows for accounting for the underlying heterogeneity in charging routines. In what follows we first describe the H-VKT model, after which we cover the main features of the H-HD model employed to analyse inter-charging duration as well as explain how the two frameworks are econometrically jointed.

### 3.1. The H-VKT model

Consider an individual $n$ ($n = 1, \ldots, N$) who is observed to undertake ($t_n = 1, \ldots, T_n$) charging events with inter-charging duration of $s_{nt}$ between charging episodes, and who travels a distance $VKT_{snt}$, then

$$\ln(VKT_{snt}) = \beta' x_{snt} + \eta_n + \xi_{snt}, \tag{1}$$

$$\xi_{snt} \sim N(0, \sigma).$$

In Eq. (1), $x_{snt}$ is a vector of explanatory variables that describes the EV usage since the previous charging event, $\beta$ is the corresponding vector of parameters to be estimated, $\eta_n$ is a normally distributed individual-specific factor with a mean of zero and a standard deviation $\delta$, which is assumed to be independent of $\xi_{snt}$. The role of $\eta_n$ is to account for unobserved heterogeneity across EV users in vehicle usage preferences. In the above equation, the dependent variable, $VKT_{snt}$, is expressed in a logarithm form. Doing so enables to accurately accommodate the asymmetric nature of the kilometres (km) travelled (i.e., $VKT_{snt}$) under examination. Given that $\xi_{snt}$

follows a normal distribution, the probability density function that the travel distance between charging events is $VKT_{snt}$ can be written as

$$\mathrm{Prob}_{H-VKT_{snt}}\left[VKT_{snt}|\beta,\delta,\sigma^2\right] = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{1}{2\sigma^2}(VKT_{snt} - (\beta' x_{snt} + \delta))^2\right), \tag{2}$$

where $\beta$, $\sigma^2$ and the standard deviation $\delta$ associated with the error term $\eta_n$ are parameters to be estimated.

Then, the unconditional likelihood function for an individual $n$ who is observed within the interval charging period $s_{nt}$ to travel $VKT_{snt}$ is integrated over the probability density function of the random term $\eta_n$

$$\mathrm{L}_{H-VKT_{snt}}|\beta,\delta,\sigma^2 = \int_{\eta_n=-\infty}^{\eta_n=+\infty}\left\{\prod_{t=1}^{T}\mathrm{Prob}_{H-VKT_{snt}}\left(VKT_{snt}|\beta,\delta,\sigma^2\right)\right\}\partial(\eta_n). \tag{3}$$

### 3.2. The H-HD model

Over the past few decades, models of duration have been widely adopted for the analysis of inter-episode time duration in transport (e.g., Schönfelder and Axhausen, 2001; Axhausen, et al., 2002; Bhat et al., 2004; Bhat et al., 2005; Arentze and Timmermans, 2009; Rasouli and Timmermans, 2014; Kim et al., 2017). Within this context of application, two distinct hazard-based duration models are used to examine the charging behaviour of irregular and regular chargers. These two latter groups are in turn identified via the class assignment probability method (Bhat, 1997). Here, irregular chargers are defined as EV drivers who charge their vehicle irrespective of the time elapsed since the last charging event, whilst regular chargers are assumed to charge their EVs at consistent intervals. First to be described is the model of duration for irregular chargers, after which attention is given to that for regular chargers.

#### 3.2.1. The H-HD model for irregular chargers

Let the hazard on the $t^{\text{th}}$ day since the previous recorded charging event for an individual $n$ and $\lambda(s_{nt})$, be defined as the conditional probability that individual $n$ will charge the EV vehicle on the $t^{\text{th}}$ day under the assumption of not having charged it before then, such that

$$\lambda(s_{nt}) = \lambda_0\exp(-\gamma' z_n - \kappa_n - \rho BU_{snt}), \tag{4}$$

where $\lambda_0 > 0, BU_{snt} = [\ln(\widehat{V}KT_{snt}) - \ln(VKT_{ndr})]$ and $VKT_{ndr}$ the vehicle driving range of the vehicle owned by individual $n$ as reported by the vehicle manufacturer.

In the above equation, $\lambda_0$ represents the constant hazard (i.e., the charging activity frequency is assumed not to vary across irregular chargers), $z_n$ is a vector of explanatory variables that characterizes owner $n$, $\gamma$ is a vector of associated parameters to be estimated, $\kappa_n$ is a normally distributed random term with mean zero and standard deviation $\alpha$, the role of which is to capture unobserved heterogeneity across irregular chargers. $BU_{snt}$, the computed difference between $\ln(\widehat{V}KT_{snt})$ and $\ln(VKT_{ndr})$, corresponds to the battery usage prior to the occurrence of the successive charging event with $\widehat{V}KT_{snt}$ being obtained from the estimation of the VKT regression model, and $\rho$ is the corresponding parameter to be estimated. The exponential functional form that we impose in Eq. (4) implies that the impact of the unobserved and observed covariates is multiplicative on the baseline constant hazard $\lambda_0$, as well as assures the positivity of the hazard function be retained during the optimization of the likelihood function.

The proportional hazard function shown in Eq. (4) can be re-written as (see Bhat, 2000)

$$\ln\int_{t=0}^{T}\lambda_0\partial t = \ln(\lambda_0 s_{nt}) = \gamma' z_n + \kappa_n + \rho BU_{snt} + \zeta_n, \tag{5}$$

where $\zeta_n$ is an extreme value distributed error term with distribution function $\mathrm{Prob}(\zeta_n < a) = G(a) = 1 - \exp(-\exp(a))$.

Assuming that $s_{nt}$ is the inter-changing time duration prior to the next charging episode for the EV charger $n$, the probability distribution function, conditional on $\kappa_n$, is then given by

$$\begin{aligned}&\mathrm{Prob}_{H-HDn|irregular}[e_n = s_{nt}|\kappa_n] = \mathrm{Prob}[\ln(\lambda_0(s_{nt}-1)) < \ln(\lambda_0 t_n) < \ln(\lambda_0 s_{nt})]\\ &= G[\ln(\lambda_0 s_{nt}) - \gamma' z_n - \kappa_n - \rho BU_{snt}] - G[\ln(\lambda_0(s_{nt}-1)) - \gamma' z_n - \kappa_n - \rho BU_{snt}].\end{aligned} \tag{6}$$

Next, the likelihood function for the irregular charger $n$ with $T_n$ charging instances, conditional on $\kappa_n$ can be formalized as

$$\begin{aligned}&\mathrm{L}_{H-HDn|irregular}|\kappa_n\\ &= \prod_{t=1}^{T}\{G[\ln(\lambda_0 s_{nt}) - \gamma z_n - \kappa_n - \rho BU_{snt}]\} - G[\ln(\lambda_0(s_{nt}-1)) - \gamma' z_n - \kappa_n - \rho BU_{snt}].\end{aligned} \tag{7}$$

Finally, the unconditional likelihood function for the irregular EV charger $n$ with $T_n$ inter-charging instances, integrated over the probability density function of the random term $\kappa_n$ can be written as

$$\mathrm{L}_{H-HDn|irregular}|\kappa_n = \int_{\kappa_n=-\infty}^{\kappa_n=+\infty}\left[\prod_{t=1}^{T_n}\{G[\ln(\lambda_0 s_{nt}) - \gamma z_n - \kappa_n - \rho BU_{snt}] - G[\ln(\lambda_0(s_{nt}-1)) - \gamma' z_n - \kappa_n - \rho BU_{snt}]\}\right]\partial(\kappa_n). \tag{8}$$

### 3.2.2. The H-HD model for regular chargers

In order to model charging patterns for regular chargers, we opt for a Weibull hazard parametric distribution function that relaxes the restrictive assumption of constant hazard made for irregular chargers, by allowing for monotonically increasing or decreasing duration dependence (Bhat, 2000). In doing so, we explicitly recognize that there exists a degree of time dependence between consecutive recharges among regular chargers. The hazard duration function for the EV driver $n$ can hence be written as

$$\phi(s_{nt}) = \phi_0\tau[\phi_0 S_{nt}]^{(\tau-1)}\exp(-\varpi' c_n - \nu_n - \psi BU_{snt}), \tag{9}$$

where $\phi_0 > 0$ and $BU_{snt} = [\ln(\widehat{V}KT_{snt}) - \ln(VKT_{ndr})]$.

In the above equation, $\phi_0$ is the hazard rate, $\tau$ is the shape parameter that dictates the duration dependence. If $\tau > 1$, the hazard is monotonically increasing in duration reflecting positive duration dependence whereas if $0 < \tau < 1$, the hazard is monotonically decreasing in duration reflecting negative duration dependence. Further, when $\tau = 1$ the Weibull distribution becomes an exponential distribution, and the hazard rate remains constant as time increases. The distribution is Rayleigh distributed at $\tau = 1$, and approximates a normal distribution for values of $3 \leq \tau \leq 4$, and for large values (e.g., greater than 10), approximates the smallest extreme value distribution (Nelson, 1982). If $\tau = 0$, then there is no duration dependence (constant hazard across individuals). $c_n$ is a vector of covariates attached to the EV driver $n$, $\varpi$ is the corresponding vector of parameters to be estimated, $\nu_n$ is a normally distributed error term with mean zero and standard deviation $\vartheta$, which captures heterogeneity in charging behaviour of regular chargers. $BU_{snt}$ corresponds to the battery usage before charging (see, section 3.2.1 for further details), and $\psi$ is the associated parameter to be estimated. Similar to Equation (4), we adopt a multiplicative exponential functional form for accommodating observed and unobserved covariates, thus avoiding imposing any restrictions on the parameter signs.

Next, the integrated logarithm of Equation (9) is given by

$$\ln\int_{t=0}^{T}\phi(s_{nt})\tau[\phi_0 S_{nt}]^{(\tau-1)}\partial t = \ln(\phi_0 S_{nt}) = \frac{1}{\tau}(\varpi' c_n + \nu_n + \psi BU_{snt}), \tag{10}$$

The unconditional likelihood for the regular charger $n$ with $T_n$ charging activities can then be written as

$$L_{H-HDn|regular}|\nu_n = \int_{\nu_n=-\infty}^{\nu_n=+\infty}\left[\prod_{t=1}^{T_n}\left\{\begin{array}{c} G\left[\ln(\phi_0 S_{nt}) - \frac{1}{\tau}(\varpi' c_n + \nu_n + \psi BU_{snt})\right] \\ -G\left[\ln(\phi_0(S_{nt}-1)) - \frac{1}{\tau}(\varpi' c_n + \nu_n + \psi BU_{snt})\right]\end{array}\right\}\right]\partial(\nu_n). \tag{11}$$

## 3.3. Latent segmentation

The class probability assignment method that we employ in this paper assumes that individuals are probabilistically assigned to the two user profiles under investigation (irregular chargers versus regular chargers). To do this, we make use of a binary logit structure and compute the probability of the individual $n$ charging at regular intervals as

$$Pr_{n|regular} = \frac{1}{1+\exp(-m_0)}, \tag{12}$$

where $m_0$ is a parameter to be estimated.

The final unconditional likelihood function for the EV driver $n$ may be specified as

$$L_n = Pr_{n|regular} \times L_{H-HD_{n|regular}} \times L_{H-VKT_{snt}} + \left(1 - Pr_{n|regular}\right) \times L_{H-HD_{n|irregular}} \times L_{H-VKT_{snt}}. \tag{13}$$

Finally, the log-likelihood function is given by

$$LL = \sum_{n=1}^{N} L_n. \tag{14}$$

The optimization routine of the log-likelihood function displayed in Equation (14) is programmed in Matlab release R2023a, with the Gaussian quadrature technique being used to evaluate the three single-dimension integrals involved in the estimation process. To summarize, the parameters that we estimate for the latent-based methodological approach developed in this paper are

- H-VKT model: $\beta, \delta$ and $\sigma^2$

- H-HD model for irregular chargers: $\lambda_0$,$\gamma$,$\alpha$ and $\rho$
- H-HD model for regular chargers: $\phi_0$,$\tau$,$\varpi$,$\vartheta$ and $\psi$
- Latent segmentation: $m_0$.

## 4. Data

The data used for the empirical demonstration are extracted from the MOP, which is a longitudinal national travel survey annually administered to a representative sample of German speaking households since 1994 (https://mobilitaetspanel.ifv.kit.edu). The survey is officially commissioned and sponsored by the German Federal Ministry for Digital and Transport. The following control variables are employed to draw the sample of households: built environment in which the household is located (core areas with over 100,000 inhabitants, peripheral areas with over 100,000 inhabitants, communities with 20,000 to 100,000 inhabitants, communities with 5,000 to less than 20,000 inhabitants, communities with fewer than 5,000 inhabitants), household structure (size, number of children and professional activities) and car ownership levels. Sample frames consists of both land and mobile phone rosters. Approximately one third of the recruited participants rotates across the annual waves, such that each respondent is surveyed no more than three times in a row. Details on the sampling design and the survey implementation can be found in the report annually released by the firm overseeing the fieldwork (KANTAR, 2022).

Each MOP wave encompasses two distinct data collection processes that are typically performed at two different moments of the year, namely autumn and spring. In autumn, each member of the sampled households (aged 10 and above) is required to fill out a one-week travel diary wherein every single trip made is recorded. The usual sociodemographic characteristics of both households and individuals are collected at this stage as well. Those households who indicate that they own at least one vehicle are then invited to participate in the successive spring survey, which is specifically designed to collect information with respect to VKT and refuelling/EV charging behaviour related to each vehicle of the household fleet over the course of eight weeks, i.e., from April to June. Specifically, households are asked to fill out a pencil-paper based vehicle usage logbook, one for each automobile of the household used for private and/or work activities. Specifically, households are asked to provide information on each charging event taking place during the survey period, including charging duration (available only from recent waves), charging location, date and odometer reading, as well as information on car characteristics (e.g. year of manufacture, make, model) and usage patterns (e.g. number of users, special circumstances during the survey period). Interested readers are referred to Vallée et al. (2022) for more detailed information on the survey organisation, administration, methodology and results.

In this study, attention is restricted to analysing the charging behaviour data associated with battery electric vehicle (BEV) owners collected between 2018 and 2022 (i.e., from autumn 2018 − spring 2019 until autumn 2021 − spring 2022). Data that are used in the present study are extracted from the spring survey, coupled with the sociodemographic information of the households collected during the autumn questionnaire administered within the same wave. Past waves are excluded from the investigation undertaken due in part to the low diffusion of BEVs during earlier periods as well as in part due to substantial changes being made to the structure of the survey body over time.

The data preparation process resulted in 2,898 charging observed instances related to 154 households over the four waves. By construction, all German households owning a BEV at the time of the survey had a known and greater than zero probability of being sampled, so that the key condition for statistical inference, namely working with a sample that is representative of the targeted reference universe, is met. However, the 154 identified households cannot be considered as representative of car owning households, and hence results from our research can be referred to BEV owning households only. Table 1 displays that the number of sampled BEV owners in the survey has rapidly increased over time, growing from seven to 90 in the latest wave. Despite this increment, there still exists a notable disparity between BEV and traditional passenger vehicle owners, with the former on average making up only 2.05 percent of the sample across four waves.[2]

### 4.1. Household sample description

Table 2 outlines the descriptive statistics pertaining to the sample of BEV users under study. Of the 154 households selected, only 28 (18.2 percent) can be classified as single person households with families surveyed being predominantly childless (131 out of 154). Most of the family units reside in urban areas (72.7 percent), own two vehicles and have access to private EV home charging infrastructure (129 out of 154 households). The largest proportion of battery electric cars are new vehicles, with almost 85 percent of respondents having owned the vehicle for no more than three years. From the table we can also deduce that the most preferable vehicle body purchased is either mini or small car (see the German Federal Motor Transport Authority for the official vehicle body classification at https://www.kba.de/EN/Home/home_node.html), that are proportionally much more prevalent than within the average German household vehicle fleet. Besides, more than three quarters of BEVs are considered the primary vehicle of the household, thus playing a prominent role in satisfying mobility needs of the residents. Lastly, 86 percent of households were recruited to take part in the MOP during the Covid-19 pandemic, i.e., the latest two waves of the MOP data set analysed herein were administered in the middle of the Covid-19 pandemic.

[2] Despite the longitudinal nature of the MOP dataset, only a negligible percent of households owning a BEV (less than three percent) took part to at least two consecutive waves. This is due to the fact that BEV diffusion is very recent, as already noted. Therefore, for those households we assume that charging events across different waves are independent one another.

**Table 1**
MOP sample sizes (overall and BEV owners).

| MOP wave | #Sampled Households | BEV owners | % of BEV owners |
|---|---|---|---|
| 2018–19 | 1,845 | 7 | 0.38 % |
| 2019–20 | 1,853 | 15 | 0.81 % |
| 2020–21 | 1,963 | 42 | 2.14 % |
| 2021–22 | 1,840 | 90 | 4.89 % |

**Table 2**
Descriptive statistics of BEV users.

| | Number | Frequency |
|---|---|---|
| Single person household | | |
| *No* | 126 | 81.8 % |
| *Yes* | 28 | 18.2 % |
| Presence of children | | |
| *No* | 131 | 85.1 % |
| *Yes* | 23 | 14.9 % |
| Type of region | | |
| *Urban* | 112 | 72.7 % |
| *Rural* | 42 | 27.3 % |
| Number of cars in the household | | |
| *1* | 52 | 33.8 % |
| *2* | 82 | 53.2 % |
| *>=3* | 20 | 13.0 % |
| Availability of an EV charger at home | | |
| *No* | 25 | 16.2 % |
| *Yes* | 129 | 83.8 % |
| BEV age | | |
| *0–3 years* | 130 | 84.4 % |
| *4–6 years* | 17 | 11.0 % |
| *>=7 years* | 7 | 4.5 % |
| BEV body: Mini or small car | | |
| *No* | 91 | 59.1 % |
| *Yes* | 63 | 40.9 % |
| BEV ordering number in the household | | |
| *First car* | 118 | 76.6 % |
| *Second car* | 34 | 22.1 % |
| *Third car* | 2 | 1.3 % |
| Covid-19 | | |
| *Yes* | 132 | 85.7 % |
| *No* | 22 | 14.3 % |

### 4.2. BEV charging patterns

Fig. 1 depicts the distribution of the inter-charging duration (days) together with related descriptive statistics for the 2,898 charging events that are contained in the dataset. The histogram shows a positively skewed distribution with a large mass (around 80 percent of the distribution) located between one and three days, suggesting that the majority of charging instances occur within three days from the previous charging event at the most. The range of the inter-charging duration distribution is 42 days, and the average charging interval is 3.23 days (around 2.17 recharges per week) with a median value of two days and a standard deviation of 4.14 days. Note that charging instances undertaken within the same day were assigned to the timeframe of *1 day* given that no information was available with respect to the time of the day the charge occurred (around less than ten charging activities were recorded to be performed within the same day of the week).

As mentioned in the methodology section, we consider charging events in a survival analysis framework. Table 3 provides related information, considering charging intervals of 1, 3, 6, 9, 15, 20, 25 and 37 days, respectively. The column of the table labelled *number at risk* represents the number of charging events that can potentially end at time *t*, the third column *Number of event* refers to the charging events that terminate at time *t*, and the fourth column *Survival Probability* corresponds to the estimated survival probabilities calculated with the Kaplan-Meir (KM) nonparametric estimator (see Kiefer, 1988), with such probabilities being also displayed in the stairs graph shown in Fig. 2.

The survival probability is reported to be more than 80 percent after nine days from the beginning of the survey, suggesting the underlying presence of positive inter-charging duration dependency. It further appears that 17 charging episodes are still potentially

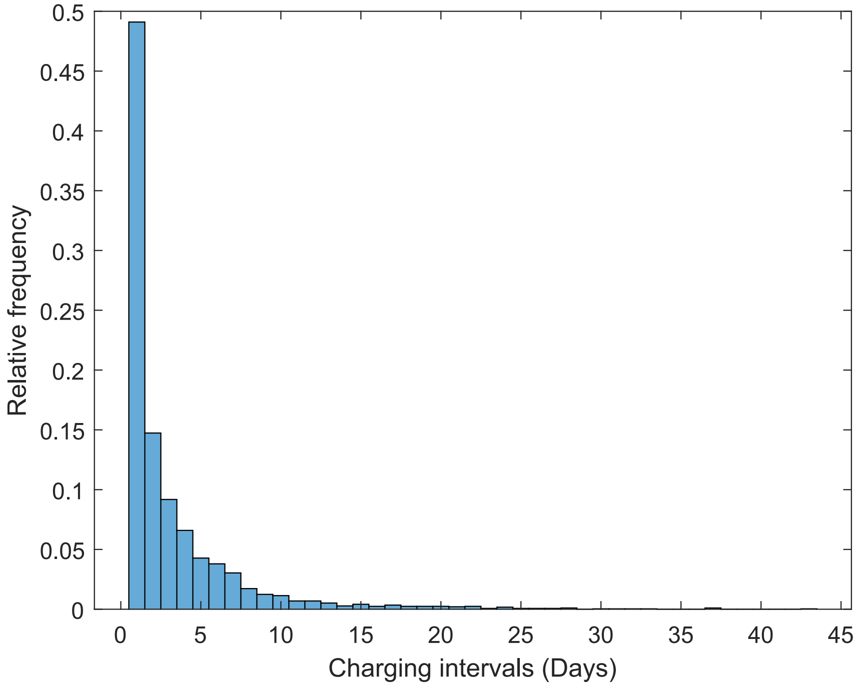



**Fig. 1.** Distribution of charging intervals (days).

**Table 3**
Inter-charging duration.

| Charging Intervals (Days) | Number at risk | Number of events | Survival Probability | Std. error | Lower 95 % CI | Upper 95 % CI |
|---|---|---|---|---|---|---|
| 1 | 2,898 | 43 | 0.99 | 0.002 | 0.98 | 0.99 |
| 3 | 1,048 | 29 | 0.96 | 0.005 | 0.95 | 0.97 |
| 6 | 467 | 33 | 0.91 | 0.010 | 0.89 | 0.93 |
| 9 | 219 | 24 | 0.83 | 0.018 | 0.80 | 0.87 |
| 15 | 87 | 13 | 0.75 | 0.028 | 0.70 | 0.81 |
| 20 | 44 | 7 | 0.66 | 0.041 | 0.59 | 0.75 |
| 25 | 17 | 3 | 0.59 | 0.056 | 0.49 | 0.71 |
| 37 | 4 | 2 | 0.41 | 0.128 | 0.22 | 0.75 |

subject to termination at the 25th day, reflecting perhaps a degree of charging regularity among BEV users.

Fig. 3 shows the distribution of the battery's state of charge prior to the successive charge. The battery usage (BU) results from dividing the VKT between consecutive charging episodes by the vehicle driving range stated by the manufacturer.[3] As seen from the graph, the highest peak (around 20 percent of the distribution) is localized between 40 percent and 45 percent indicating that there is a clear tendency of EV users charging their electric cars in spite of the battery being less than half empty. Around 11 percent of charging events occur in what could be considered an emergency condition, i.e., when the state of charge of the battery is 10 percent or lower.

## 5. Results

Various model specifications were tested prior to identifying that reported in Table 4, associated with the model structure that returns the best goodness of fit. Table 4 is structured as follows. The first main block illustrates the empirical findings obtained from the estimation of the H-VKT model. The second main block of results displays the estimated parameters associated with the two H-HD models used to estimate charging patterns for regular and irregular chargers, whilst the third block of information describes the segment sizes of the two BEV charging groups. The fourth and final block within the table outlines goodness of fit measures, which demonstrate that the inclusion of household and vehicle characteristics assists in understanding the charging routine of BEV users better, as shown by the improvement of the likelihood function at convergence.

With respect to the observed covariates used for estimation, four dummy variables are adopted for investigating BEV usage between

[3] The BU serves as a proxy here for the SOC give that the latter was not captured as part of earlier waves within the survey. Further, we assume that discharge/charge cycle results in the vehicle being fully charged.

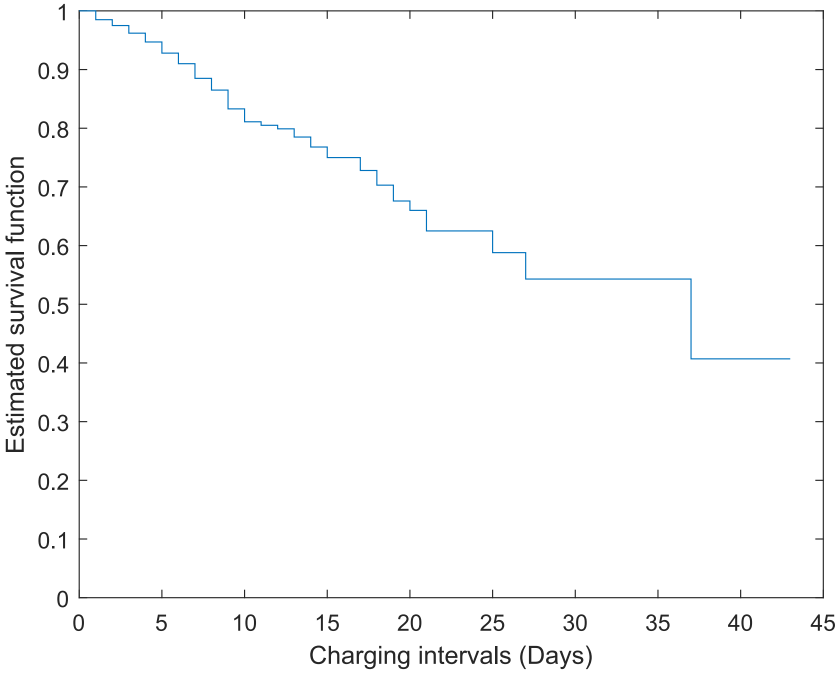
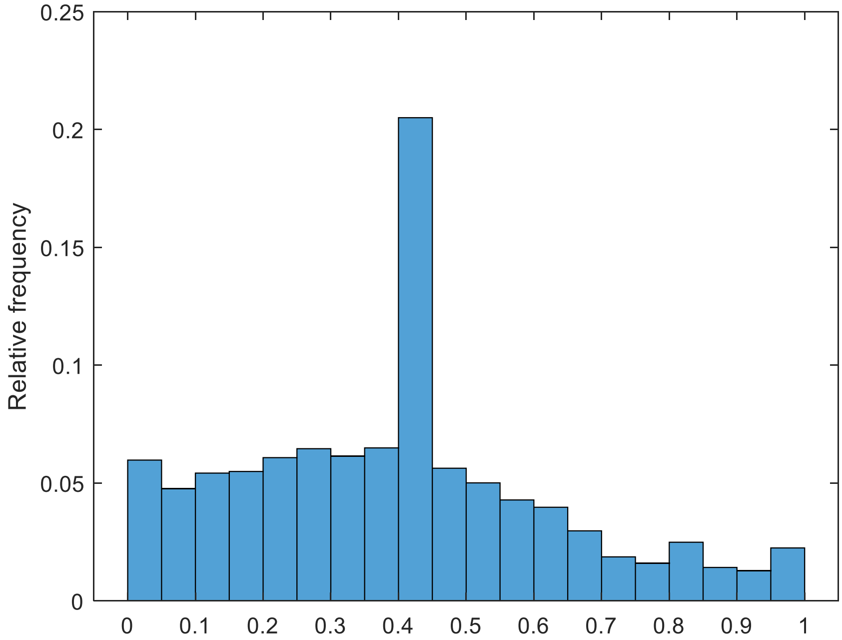



**Fig. 2.** Kaplan Meir Survival function.




| Descriptive statistics: Battery usage (BU) before charging | |
|---|---|
| Mean | 0.40 |
| Median | 0.42 |
| Mode | 0.42 |
| Standard deviation | 0.23 |

**Fig. 3.** Distribution of BU before charging.

**Table 4**
Estimation results.

| | H-VKT model | | | |
|---|---|---|---|---|
| | Parameter | | (*t*-stat) | |
| Intercept | 1.34 | | (19.48) | |
| Scale ($\sigma$) | 0.74 | | (74.62) | |
| Individual specific error term ($\delta$) | 0.80 | | (38.83) | |
| Home charging station (No is base) | 0.11 | | (2.37) | |
| Vehicle age (age > 3 years is base) | 0.23 | | (4.59) | |
| Main car of the household (No is base) | 0.18 | | (4.66) | |
| Type of region: Rural (Urban is base) | 0.13 | | (2.34) | |
| | H-HD model | | | |
| | Irregular Chargers | | Regular Chargers | |
| | Parameter | (*t*-stat) | Parameter | (*t*-stat) |
| Hazard rate ($\lambda_0$) | 1.13 | (6.82) | – | – |
| Individual specific error term ($\alpha$) | 0.98 | (22.87) | – | – |
| Hazard rate ($\phi_0$) | – | – | 0.20 | (5.78) |
| Shape parameter ($\tau$) | – | – | 2.10 | (14.18) |
| Individual specific error term ($\vartheta$) | – | – | 1.57 | (9.41) |
| Mini or small car (No is base) | 0.28 | (2.69) | −0.70 | (−4.15) |
| #Cars in the household | 0.19 | (5.37) | – | – |
| Single person household (No is base) | 0.02 | (0.20) | – | – |
| Presence of kids (No is base) | −0.61 | (−8.58) | −1.44 | (−3.79) |
| Vehicle Age (>3 years is base) | 0.58 | (4.99) | 0.79 | (3.02) |
| Type of region: Rural (Urban is base) | – | – | −1.08 | (−4.19) |
| Covid-19 (No is base) | 0.50 | (3.99) | 1.12 | (4.11) |
| BU (link with H-VKT) ($\rho, \psi$) | −0.28 | (−8.00) | −1.64 | (−10.10) |
| | **Latent segmentation model** | | | |
| | Parameter | | (*t*-stat) | |
| $m_0$ | −1.63 | | (−5.74) | |
| | **Segmentation size** | | | |
| Irregular chargers | 83.56 % | | | |
| Regular chargers | 16.44 % | | | |
| Number of BEV users | 154 | | | |
| Number of charging instances | 2898 | | | |
| Number of estimated parameters | 26 | | | |
| Initial log-likelihood | −16784.67 | | | |
| Log-likelihood at convergence | −8112.24 | | | |
| Akaike information criterion (AIC) | 16276.52 | | | |
| Bayesian information criterion (BIC) | 16431.79 | | | |

charging instances with these regressors being availability of an EV home charger (no is base), BEV age less or equal to three years (older than three years is base), whether the battery electric car is the main vehicle of the household (no is base), whether the type of region the household is located in is a rural area (urban area is chosen as base). The type of region and vehicle age dummy variables are also employed to assess inter-charging duration coupled with vehicle body (whether the vehicle is either a mini or a small, or not), single person household (no is set as base), households with kids (childness households is treated as base), size of the household vehicle fleet and BU before charging, with the latter two covariates being continuous in nature. The last variable included in the H-HD models is a dummy variable which takes the value of one if the data collection was performed during the Covid-19 pandemic, zero otherwise. Note that we rescale the VKT by ten in such a way as to prevent potential instability problems in the optimization of the likelihood function. In what follows, we first focus on the H-VKT model after which we discuss at length the empirical findings of the two H-HD models.

### *5.1. H-VKT results*

Overall, the estimates of the H-VKT model have the expected signs and provide interesting insights into vehicle usage preferences between charging episodes. It is worth mentioning that the impact of the $k^{\text{th}}$ regressor can be measured as the percent change in the dependent variable, VKT, resulting from a one-unit variation in the $k^{\text{th}}$ regressor by applying the formula, $[\exp(\beta_k) - 1] \times 100$. Specifically, both the intercept and the scale are found to be statistically significant with the latter reflecting the existence of dispersion around the mean VKT. The individual specific error term is estimated to be highly statistically significant and hence we can conclude that there exists heterogeneity in vehicle usage behaviour across respondents.

The estimated parameter associated with the EV home charging infrastructure variable is statistically significant and positive, suggesting that the ownership of an EV home charger increases the distance travelled between consecutive charging occurrences by approximately 11.4 percent ($[\exp(0.11) - 1] \times 100$), *everything else being equal*. In a similar vein, the production age of the vehicle seems to affect the distance travelled prior to the next charge. Specifically, the positive and statistically significant parameter for the dummy variable *BEV age* (older than three years is base) indicates that owners of newer battery electric cars tend to drive more (+25.8 percent) before charging occurs as opposed to owners of older BEVs who charge their vehicles more frequently. This result is presumably due to the extended driving range that characterises more recently manufactured BEVs. The third explanatory variable listed in the first block of the table accounts for the primacy of the vehicle within a household's vehicle fleet inventory. As the corresponding coefficient is positive and statistically significant, we can assert that the usage of a vehicle increases (+19.9 percent) with its importance within the household. The last observed covariate included in the model specification relates to the type of region respondents reside in (urban area is treated as base). As seen in the table, those households who reside in rural areas appear to drive more (about 14 percent more) prior to charging the vehicle relative to their urban counterparts. This might be due to the fact that rural residents have typically longer daily trip chains than those who reside in more urban areas.

### 5.2. H-HD results

Now we turn our attention to the model parameter estimates that stem from the implementation of the heterogenous hazard-based duration models for irregular and regular chargers. Given the functional form specified in Equations (4) and (7), a positive (negative) estimated coefficient implies that the corresponding covariate increases (decreases) the inter-charging duration, resulting in a lower (higher) frequency of charging, *everything else being equal*. Further, the impact of a covariate on the duration hazard for irregular chargers can be calculated as $\left[\exp\left(\gamma_f\right) - 1\right] \times 100$ for a one unit change in the $f^{th}$, whereas the percentage variation in the hazard duration due to a one unit change in $f^{th}$ variable in the regular charging group is given by $\left[\exp\left(\frac{\varpi_f}{\tau}\right) - 1\right] \times 100$, where $\tau$ accounts for underlying duration dependence across charging patterns.

The hazard rate for irregular chargers is found to be statistically significant with a value of 1.13 whilst that for regular chargers it is 0.20. The shape parameter of the Weibull parametric hazard model is reported to be statistically significant and larger than one ($\tau$=2.10) suggesting that there is temporal regularity in the charging behaviour of regular chargers (i.e., regular chargers appear to recharge their vehicles at unvarying intervals). Individual random terms for both irregular and regular chargers are statistically sig-

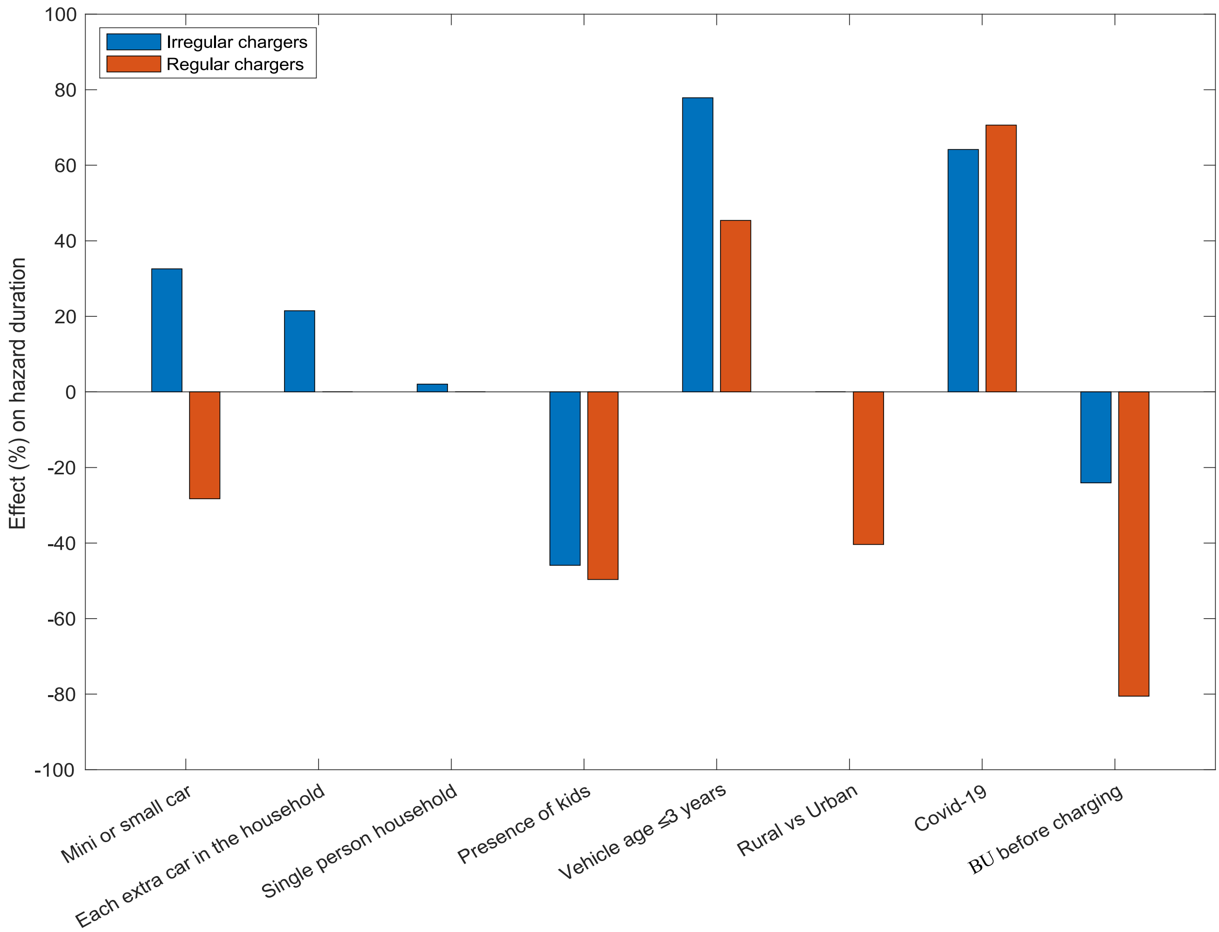



**Fig. 4.** Effects on hazard duration.

nificant, revealing the existence of unobserved factors that influence the time duration between successive charging activities. Of particular interest, however, is the computation of the contribution that unobserved factors have to the variation in the hazard duration (Bhat, 2004). This can be calculated for irregular chargers as $\frac{Var(\alpha)}{Var(\alpha)+Var(\gamma' z_n+\rho BU_{snt})}$ and for regular chargers as $\frac{Var(\vartheta)}{Var(\vartheta)+Var\left(\frac{1}{\tau}[\varpi' c_n+\psi BU_{snt}]\right)}$. The fraction of variation of irregular chargers is estimated to be approximately 70.26 percent compared to 22.83 percent for regular chargers. From this result, we can conclude that it is more difficult to investigate the charging behaviour of irregular chargers than it is to explore the behaviour of regular chargers (i.e., there is a larger degree of heterogeneity in the charging frequency behaviour amongst irregular chargers than is observed amongst regular chargers). Lastly, the class assignment probability used for the identification of the two charging groups (presented within the third block of the table) reveals that approximately 84 percent of households are more likely to charge the automobile at irregular intervals, whilst 16 percent have regular charging routines.

#### 5.2.1. Impact of explanatory variables on hazard duration

To better understand the magnitude effect of observed covariates, we plot in Fig. 4 the percentage change in the hazard duration for both irregular and regular chargers computed as described above. The first variable, vehicle body, is based on a dummy variable taking the value of one if the electric car is either small or mini, or zero otherwise. From the figure, it is clear that there exists two opposing charging practices occurring within the sample. Whilst regular chargers tend to frequently charge their vehicle, whether the vehicle is a mini or small BEV, irregular chargers appear to prolong the time before engaging in charging activities by up to 30 percent more than the overall average. Jointly considering the behaviour of the two groups, irregular charges who drive mini or small cars have a charging interval that is approximately 61 percent longer compared to regular charging mini or small car owners.

The size of the household fleet seems to positively affect the hazard duration in the irregular charging segment, meaning that the inter-charging duration spell increases by approximately 22 percent for each additional vehicle available in the household fleet. Counter to this, the presence of children within a household negatively influences the hazard duration for both segments, suggesting that households with children have a higher charging frequency compared to childless households. Next, owners of newer BEVs, (i.e., vehicles owned by the households at the time of the survey for no more than three years) charge less often relative to owners of older vehicles, with irregular chargers showing a much lower charging interval period than regular chargers.

With respect to the magnitude effect of the type of region on hazard duration, we find that the charging interval for regular chargers residing in rural areas reduces by around 40 percent compared to that of regular chargers living in urban areas. No such effect is observed for irregular charging households. Next to be considered is the Covid-19 dummy variable which captures how the Covid-19 pandemic influenced the charging decision-making process of BEV users. The estimated findings suggest that the inter-charging duration increases during the Covid-19 pandemic, with similar patterns being detected between the two BEV groups under assessment. The BS before charging is found to negatively influence the hazard duration for both segments, with the duration between charging episodes decreasing by 24 percent for irregular chargers and by 80 percent for regular chargers respectively, based on a 10 percent increment in the battery use (the magnitude of the estimated coefficients reflects the fact that the VKT is rescaled by ten). Further, the statistical significance of the two parameters related to BS confirms the underlying link between the two econometric models developed in this study.

#### 5.2.2. Charging behaviour of irregular and regular chargers

As shown in Table 5, the average interval duration for irregular chargers amounts to around 4.1 days, almost 1.5 times larger than that for regular chargers. This suggests that regular chargers are inclined to recharge their electric cars more frequently than what irregular chargers do (almost twice a week). This finding is consistent with the inter-charging duration of 2.7 days reported in Kim et al. (2017), albeit the authors only investigated public transaction charging data. The weighted sample average for inter-charging duration is approximately four days (similar to the average charging interval of 3.23 days observed within the data), with weights being the estimated segmentation dimensions of the two identified charging groups. A further finding relates to driving behaviour of BEV users. From the table, regular chargers tend to drive more prior to charging their vehicle, with a daily VKT between charging instances of 33 kms, whereas irregular chargers tend to travel on average around 22.5 kms per day before charging the vehicle. Lastly, the proposed methodological framework allows for calculating the BU before charging for the sample of BEV users under assessment. This is done via the computation of the ratio between the predicted average of VKT for the entire sample and the average driving range declared by the automobile manufacturer, the value of which stands at 269 km. We find that the battery usage between charging episodes is around 35 percent meaning that, despite more than 65 percent charge remaining, drivers are presumably concerned with respect to the distance the electric car can further travel for (i.e., range anxiety).

#### 5.2.3. H-HD model application: Scenarios of future BEV charging behaviour

In this section, we discuss the results obtained from two different simulated exercises. The first undertaken simulation (Fig. 5) investigates potential changes in charging intervals in response to upgrades in the driving range capacity of BEVs, whereas the second simulation shows how the charging routine of EV drivers will evolve due to variations in the VKT between charging episodes

**Table 5**
Predicted charging and driving patterns.

| | Average inter-charging duration (days) | Daily VKT between charging episodes | BU before charging |
|---|---|---|---|
| Irregular chargers | 4.11 | 22.48 | – |
| Regular chargers | 2.77 | 33.44 | – |
| Weighted sample | 3.88 | 24.28 | 34.33 % |

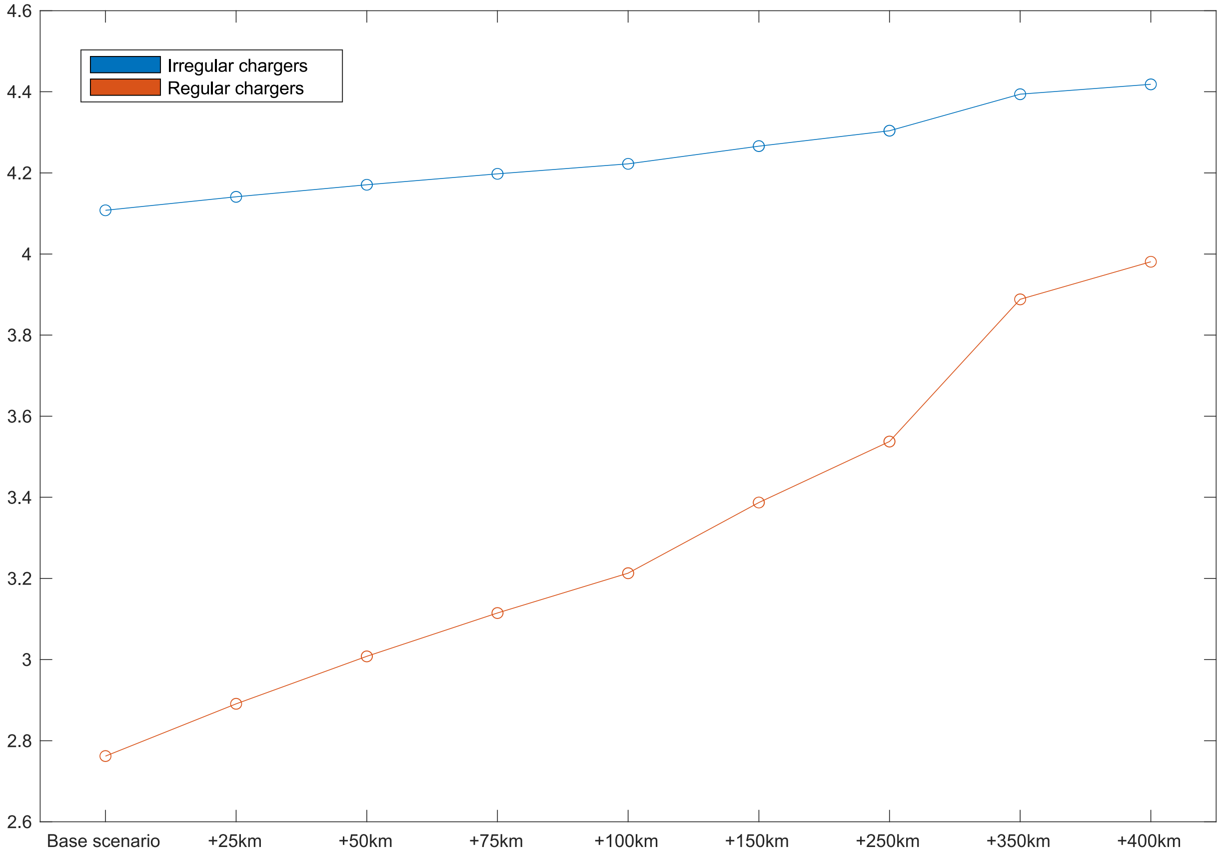



**Fig. 5.** Variation in charging intervals due to augmented driving ranges.

(Table 5).[4]

***Simulation 1: Increase of BEV driving ranges***

Results from the first simulation are presented in Fig. 5. On the $x$-axis, we report the base scenario (from Table 5) alongside eight simulated increments of driving ranges that could potentially be claimed by manufactures, spanning from + 25 kms to + 400 kms (note that the base scenario, on the $x$-axis origin, assumes an average driving range of 269 kms). A potential increment of up to 400 kms is included so as to simulate a future vehicle market whereby BEVs have the same driving range as current ICE vehicles. The $y$-axis shows the average time (expressed in days) that elapses between consecutive charges, with the base scenarios for both regular and irregular chargers corresponding to the predicted inter-charging episodes obtained from the estimation of the modelling framework described in Section 2.

From the simulation results, the inter-charging duration of irregular chargers shows a steady growth as the driving range of the vehicle increases. Specifically, a predicted driving range of 669 km (base scenario of 269 km + 400 km) is estimated to increase the elapsed time between charging instances for EV irregular charges by 7.6 percent (1.70 charging events per week). Turning the attention to EV regular chargers, the charging occurrence of this segment is predicted to be substantially influenced by potential improvements in the driving range of BEVs, with the frequency of charging being predicted to drop from 2.5 to 1.75 charging events

[4] In this study, we also explored two further scenarios a) each household owns a private home EV charger, and b) all BEVs are assumed to be the main vehicle of the household. However, none of the simulated results showed significant variations in inter-charging behaviour for both regular and irregular chargers.

per week. From this, we can conclude that the differences in charging activities between the two investigated EV charging types are foreseen to decrease, should technological innovations contribute to the manufacture of batteries that enable longer travel distances.

***Simulation 2: Variation in VKT between charging events***.

The second simulated policy explores changes in the charging behaviour of the two groups (regular chargers and irregular chargers) under different amounts of kilometres travelled. This scenario reflects, for example, the impact on transport systems given possible changes in urban design. For instance, the concept of 15-minute cities where residents of an area are able to perform key activities in their life, such as working, shopping, education and recreation, all within a short walk, bike, or transit ride from their home, is designed to reduce the amount of travel necessary, and hence hopefully results in a reduction in VKT for trips taken with motorised private means too. Fig. 6 displays the simulated findings for regular and irregular chargers resulting from a variation of ± 5 km (up to ± 20 km) in the VKT travelled between charging episodes compared to the base scenario, with the latter being (again) the outcome of the models proposed as per the previous simulation (see Table 5).

As shown in Fig. 6, the charging routine of irregular chargers (who are the vast majority of the sample) is found to be largely unaffected by changes in the VKT. Indeed, the inter-charging duration is predicted to increase by only 1.12 percent in response to a daily reduction of 20 km in the VKT. On the other hand, we observe that the elapsed time between charging episodes for regular chargers will increase by around 6.4 percent if VKT decreases by 20 kms per day. This suggests that for this segment of EV owners, moving services closer to where they live will have a relevant influence on their charging preferences.

Increasing the amount of travel undertaken is also predicted to have only a limited impact on the charging behaviour of the irregular charging segment of the population, with a 20 km addition of travel per day decreasing the charging interval by only 0.92 percent. On the contrary, increasing the distance travelled by those belonging to the regular charging segment of the population decreases the inter-charging interval by 5 percent.

Interestingly, for both segments, the predicted impact on inter-charging duration is non-symmetrical around increases and decreases in travel, with decreases in travel having a larger impact (as a percentage change) on charging duration than does increases in travel. With respect to the impact on energy grids and energy markets, this supports the concept of either moving essential as well as desirable services and activities closer to where individuals reside (thus increasing the land use mix) or improving accessibility to such activities in such a way as to minimise the distances needed to be travelled.

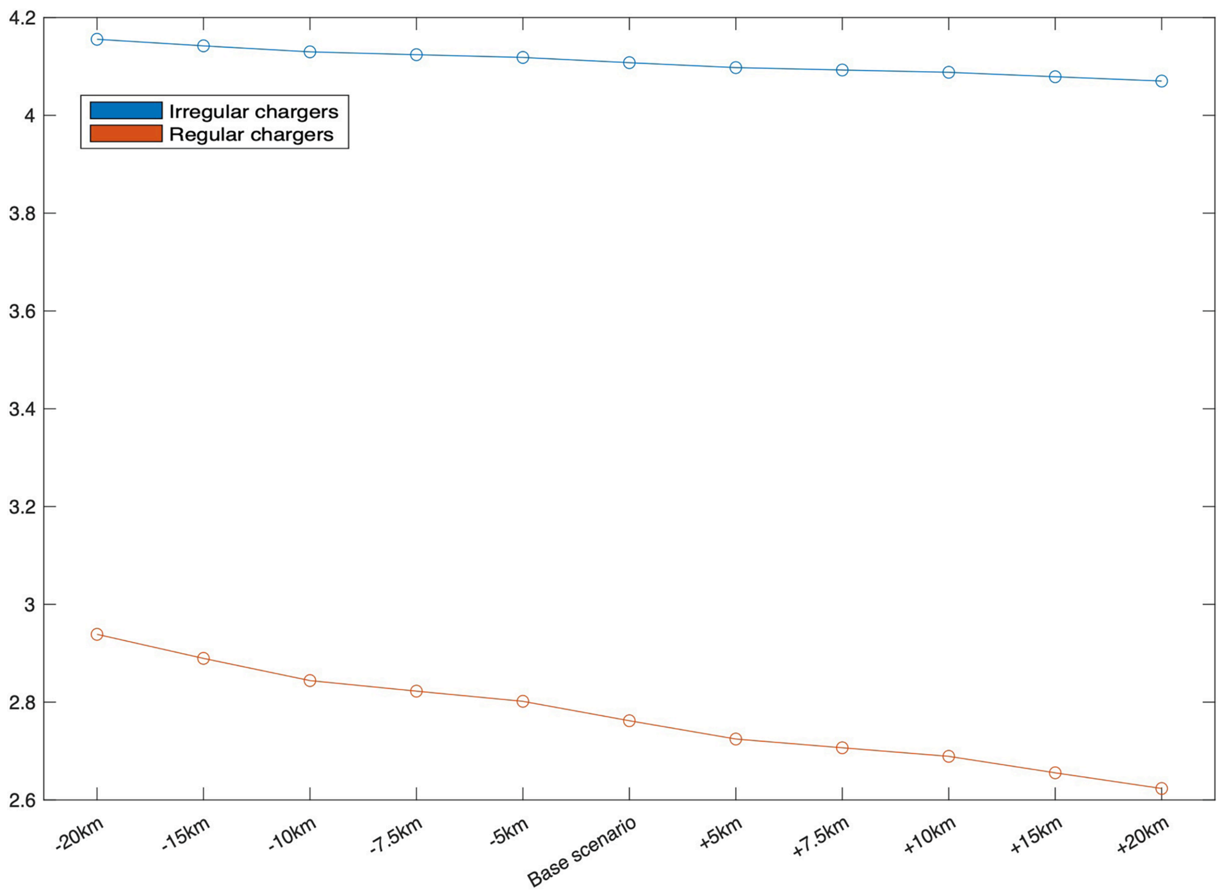



**Fig. 6.** Variation in charging intervals due to VKT changes.

## 6. Conclusions

This study has considered observational data from a representative sample of EV owners in Germany that reported on their mileage and EV charging behaviour over eight weeks. BEV charging patterns and related VKT and battery usage were studied through a survival analysis framework and modelled through a hazard-based model for charging intervals coupled with a regression model for predicting VKT. Furthermore, latent classes were considered to distinguish between regular and irregular charging behaviour displayed by different EV owners.

Almost half of the observed charging intervals are one day apart, with an average value of 3.23 days. In most of these cases, the battery is estimated to be at least half full, whereas the battery usage was found to be less than 10 percent in 11 percent of charging events. On the other hand, the models presented reveal that VKT between charging intervals is positively affected by the availability of an EV home charger, using a newer vehicle, considering the BEV as the main vehicle in the household, and whether the owner lives in a rural area. BEV vehicle ranges are dependent not only on the technology performances, but also on the actual conditions of use of such vehicles for which our models give the above interesting insights.

Charging frequency and patterns were found to be radically different between regular and irregular chargers, who are about 17 percent and 83 percent of the sample respectively. Regular chargers typically charge their vehicles 1.5 times more frequently, i.e., less than three days on average. Besides, a 10 percent decrement of the battery usage implies an increase of the frequency of charging of 80 percent by regular chargers, but only of 24 percent by irregular chargers.

Lastly, these models were applied to develop scenarios aimed at understanding how charging intervals will change due to both technology evolution (namely, an improvement of BEV driving ranges) and user-centric factors (VKT variations). The development of the charging infrastructure is one of the key issues to tackle in view of the massive diffusion of BEV. It is therefore paramount to set up quantitative methods to forecast charging frequencies and in turn plan for an adequate number of charging points, as BEV fleets performances and usages evolve over time. According to the estimated scenarios, neither technological nor user factors are predicted to substantially impact the inter-charging duration behaviour of irregular chargers. Unfortunately, these latter individuals reflect the largest segment of BEV owners under study, suggesting that little can be done to change how and when this segment is likely to charge their vehicles. On the other hand, relative to regular chargers, the irregular charging group tends to charge their vehicles at greater intervals, and as such, are likely to be of less interest to policy makers with respect to seeking to change their behaviour in order to face shortages in charging points.

Regular chargers exhibit a clear distinct behaviour. For this charging group, increasing driving range of EVs, particularly above 100 kms beyond existing vehicle ranges, will likely result in significant increases in the interval between charging instances. Likewise, efforts that result in the reduction of VKT, also are predicted to impact positively on this segment in terms of inter-charge duration spell. From a policy perspective, such increases in the elapsed time between charging events is important, as it can lead to a lower provision of needed public charging points, which represents one of the major foreseeable challenges with the widespread of BEVs .

With the growth of the BEV market, it is plausible that the observed proportion of regular versus irregular users will change, with the latter segment becoming less predominant amongst BEV owners. As a result, charging habits will become more sensitive to both technology improvements and usage patterns in the future, compared to the current situation where demand on the charging infrastructure essentially depends on the number of BEVs on roads. As such, policymakers need to account for the effect of technological advancements as well as potential behaviour changes on user charging frequencies when designing policy actions to support the widespread adoption of EVs. This paper seeks to bridge this research gap, by formalizing a framework to accurately forecast charging patterns, and the subsequent demand for charging outlets. This is done by simultaneously considering BEV diffusion, technology and usage patterns through a latent-based segmentation approach.

Whilst the study proposes a novel framework for assessing inter-charging duration spells, there are some limitations that warrant acknowledgment. Our observations encompass pandemic times, that might have altered the charging decision-making process of BEV users. To account for the effect of Covid-19 on charging behaviour, we only introduced a dummy variable which takes the value of one if the household was sampled during the Covid-19 pandemic, or zero otherwise. This means that the current model specification disregards the effect that Covid-19 related vehicle usage restrictions imposed by the Government of Germany had on mobility patterns. The inclusion of such variables would assist us in better capturing potential changes in charging behaviour within the Covid-19 pandemic timeframe. Second, the state of battery charge (SOC) was not observed in earlier waves of data. While the inclusion of (modelled) battery usage (BU) into the modelling framework represents a contribution to this paper, future research should focus on this aspect of EV ownership. For BEV using current lithium-ion batteries, it is optimal to keep the charging level of the vehicle between 20 and 80 percent, rather than allow it to be fully discharged or fully charged. This is because lithium-ion batteries work better when used and charged in partial cycles, with overuse as well as long periods of non-use with batteries at extremely high or low levels of charge can significantly decrease battery life. Further, many EVs now make use of regenerative breaking, and charging the battery to levels no higher than 80 percent allows capacity for energy generated from such a system to be properly stored. Hence, although beyond the scope of this paper, understanding how different segments of the population currently manage the BU of the EVs they own, and possibly developing strategies that enable them to optimally charge their vehicles (possibly through smart grids to optimise the overall temporal distribution of electricity demand as well) represents an important area of research, as doing so may prolong the vehicle battery life, and reduce the vehicle overall life cycle emissions produced. Of course, any attempt to influence the minimum and maximum SOC for BEV users may increase the impact of range anxiety on EV uptake, as doing so necessarily reduces the possible driving ranges of such vehicles. As such, there may exist, at least in the short term, a conflict between optimal charging behaviour designed to maximise the life of batteries in BEVs, and the perceived ability of drivers to use such vehicles as desired.

## CRediT authorship contribution statement

**Andrea Pellegrini:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Diana:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **John Matthew Rose:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors do not have permission to share data.

## References


Alexander, M., 2022. Home Charging Access in California. California Energy Commission. Publication Number: CEC-600-2022-021.

Arentze, T.A., Timmermans, H.J.P., 2009. A need-based model of multi-day, multi-person activity generation. Transportation Research Part B: Methodology, pp. 251-265.

Axhausen, K.W., Zimmermann, A., Schönfelder, S., Rindsfüser, G., Haupt, T., 2002. Observing the rhythms of daily life: a six-week travel diary. Transportation 29, 95–124.

Bhat, C.R., 1997. An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel. Transportation Science 31, 34–48.

Bhat, C.R., Frusti, T., Zhao, H., Schonfelder, S., Axhausen, K.W., 2004. Intershopping Duration: An Analysis Using Multiweek Data. Transportation Research Part b: Methodological 38, 39–60.

Bhat, C.R., Srinivasan, S., Axhausen, K.W., 2005. An Analysis of Multiple Interepisode Durations Using a Unifying Multivariate Hazard Model. Transportation Research Part b: Methodological 39, 797–823.

Bhat, C.R., 2000. Duration Modeling. In Handbook of Transport Modelling, D.A. Hensher, K.J. Button.

Chi, Y.-Y., Wang, Y.-Y., Xu, J.H., 2021. Estimating the impact of the license plate quota policy for ICEVs on new energy vehicle adoption by using synthetic control method. Energy Policy 149, 112022.

Daina, N., Polak, J.W. 2016. Hazard based modelling of electric vehicles charging pattern. Conference Paper.

Daina, N., Sivakumar, A., Polak, J.W., 2017. Electric vehicle charging choices: modelling and implications for smart charging services. Transportation Research Part c: Emerging Technologies 81, 36–56.

Das, H.S., Rahman, M.M., Tan, C.W., 2020. Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. Renewable and Sustainable Energy Reviews 120.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part c: Emerging Technologies 38, 44–55.

Franke, T., Krems, J.F., 2013a. Interacting with limited mobility resources: psychological range levels in electric vehicle use. Transportation Research Part a: Policy and Practice 48, 109–122.

Franke, T., Krems, J.F., 2013b. Understanding charging behaviour of electric vehicle users. Transportation Research Part f: Traffic Psychology and Behaviour 21, 75–89.

Funke, S.Á., Sprei, F., Gnann, T., Plötz, P., 2019. How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. Transportation Research Part d: Transport and Environment 77, 224–242.

Ghamami, M., Zockaie, A., Nie, Y., 2016. A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. Transportation Research Part c: Emerging Technologies 68, 389–402.

Ghasri, M., Ardeshiri, A., Ekins-Daukes, N.J., Rashidi, T., 2021. Transportation Research Part C: Emerging Technologies 133, 103433.

Girard, A., Roberts, C., Simon, F., Ordoñez, J., 2019. Solar electricity production and taxi electrical vehicle conversion in Chile. Journal of Cleaner Production 210, 1261–1269.

Globisch, J., Plötz, P., Dütschke, E., Wietschel, M., 2019. Consumer preferences for public charging infrastructure for electric vehicles. Transport Policy 81, 54–63.

Gnann, T., Plötz, P., 2015. A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. Renewable Sustainable Energy Review 47, 783–793.

Gong, S., Ardeshiri, A., Rashidi, T.H., 2020. Impact of government incentives on the market penetration of electric vehicles in Australia. Transport and Environment, Transportation Research Part D, p. 83.

Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., Stannard, J., 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: a qualitative analysis of responses and evaluations. Transportation Research Part a: Policy and Practice 46, 140–153.

Greaker, M., 2021. Optimal regulatory policies for charging of electric vehicles. Transport and Environment, Transportation Research Part D, p. 97.

Greene, D.L., Kontou, E., Borlaug, B., Brooker, A., Muratori, M., 2020. Public charging infrastructure for plug-in electric vehicles: What is it worth? Transport and Environment, Transportation Research Part D, p. 78.

Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. Renewable and Sustainable Energy Reviews 80, 1100–1111.

Hardman, S., Jenn, A., Gil, T., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Wikamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transportation Research Part d: Transport and Environment 62, 508–523.

Hasan, S., Simsekoglu, Ö., 2020. The role of psychological factors on vehicle kilometer travelled VKT for battery electric vehicle BEV users. Research in Transportation Economics 82.

Illmann, U., Kluge, J., 2020. Public charging infrastructure and the market diffusion of electric vehicles. Transport and Environment, Transportation Research Part D, p. 86.

International Energy Agency, 2016. International energy outlook.

International Energy Agency, 2020. International energy outlook.

International Energy Agency, 2022. International energy outlook.

Jakobsson, N., Gnann, T., Plötz, P., Sprei, F., Karlsson, S., 2016. Are multi-car households better suited for battery electric vehicles? Driving patterns and economics in Sweden and Germany. Transportation Research Part c: Emerging Technologies 65, 1–15.

Jenn, A., Springel, K., Gopal, A.R., 2018. Effectiveness of electric vehicle incentives in the United States. Energy Policy 119, 349–354.

KANTAR, 2022. Deutsches Mobilitätspanel MOP – Erhebung der Alltagsmobilität sowie der Pkw-Fahrleistungen und Kraftstoffverbräuche – Endbericht zum Paneljahr 2021/2022. https://mobilitaetspanel.ifv.kit.edu/downloads/KANTAR_Endbericht_MOP_2021_2022_inkl_Anlagen.pdf.
Khan, M., Kockelman, K., 2012. Predicting the market potential of plug-in electric vehicles using multiday GPS data. Energy Policy 46, 225–233.
Khoo, Y.B., Wang, C.H., Paevere, P., Higgins, A., 2014. Statistical modeling of electric vehicle electricity consumption in the Victorian EV Trial, Australia. Transportation Research Part d: Transport and Environment 32, 263–277.
Kiefer, N.M., 1988. Econometric Duration Data and Hazard Functions. Journal of Econometric Literature 27, 646–679.
Kim, H., Kim, D.W., Kim, M.K., 2022. Economics of charging infrastructure for electric vehicles in Korea. Energy Policy 164.
Kim, S., Yang, D., Rasouli, S., Timmermans, H., 2017. Heterogenous hazard model of PEV users charging intervals: Analysis of four year charging transactions data. Transportation Research Part c: Emerging Technologies 82, 248–260.
LaMonaca, S., Ryan, L., 2022. The state of play in electric vehicle charging services – A review of infrastructure provision, players, and policies. Renewable and Sustainable Energy Reviews 154.
Latinopoulos, C., Sivakumar, A., Polak, J.M., 2017. Response of electric vehicle drivers to dynamic pricing of parking and charging services: Risky choice in early reservations. Transportation Research Part c: Emerging Technologies 80, 175–189.
Li, Z., Ouyang, M., 2011. The pricing of charging for electric vehicles in China—Dilemma and solution. Energy 36, 5765–5778.
Liu, X., Sun, X., Zheng, H., Huang, D., 2021. Do policy incentives drive electric vehicle adoption? Evidence from China. Transportation Research Part a: Policy and Practice 150, 49–62.
Ma, S.-C., Fan, Y., Feng, L., 2017. An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions. Energy Policy 110, 609–618.
Masuda, T., Araki, K., Okumura, K., Urabe, S., Kudo, Y., Kimura, K., Nakado, T., Sato, A., Yamaguc, M., 2017. Static concentrator photovoltaics for automotive applications. Solar Energy 146, 523–531.
McNutt, B., Rodgers, D., 2004. Lessons learned from 15 years of alternative fuels experience – 1988–2003. Academic Press, San Francisco, The Hydrogen Energy Transition.
Melaina, M., Muratori, M., McLaren, J., Schwabe, P., 2017. Investing in alternative fuel infrastructure: Insights for California from stakeholder interviews. In: Proceedings of the Transportation Research Board.
Neaimeh, M., Salisbury, S.D., Hill, G.A., Blythe, P.T., Scoffield, D.R., Francfort, J.E., 2017. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. Energy Policy 108, 474–486.
Nelson, W., 1982. Applied Life Data Analysis. Addison-Wesley.
Pellegrini, A., Yao, X., Rose, J.M., Ma, S. 2023a. An autoregressive spatial stochastic frontier analysis for quantifying the sales efficiency of the electric vehicle market: An application to 88 pilot cities in China. Working paper: ITLS-WP-23-07, Institute of Transport and Logistic Studies, University of Sydney.
Pellegrini, A., Borriello, A., Rose, J.M., 2023b. Assessing the willingness of Australian households for adopting home charging stations for electric vehicles. Emerging Technologies, Transportation Research Part C, p. 148.
Pellegrini, A., Rose, J.M., 2023. Vehicle choice and use under alternative policy scenarios: What needs to be done to promote electric vehicle uptake and usage. Working paper: ITLS-WP-23-01, Institute of Transport and Logistic Studies. University of Sydney.
Rasouli, S., Timmermans, H., 2014. Activity-based models of travel demand: promises, progress and prospect. International Journal of Urban Sciences 18, 31–60.
Schönfelder, S., Axhausen, K.W., 2001. Modeling the rhythms of travel using survival analysis. Conference Paper.
Schulz, F., Rode, J., 2022. Public charging infrastructure and electric vehicle in Norway. Energy Policy 160.
Speidel, S., Bräunl, T., 2013. Driving and charging patterns of electric vehicles for energy usage. Renewable and Sustainable Energy Reviews 97–110.
Sun, X.H., Yamamoto, T., Morikawa, T., 2015. Charging timing choice behaviour of battery electric users. Transportation Research Part d: Transport and Environment 37, 97–107.
Tamor, M.A., Moraal, P.E., Reprogle, B., Milačić, M., 2015. Rapid estimation of electric vehicle acceptance using a general description of driving patterns. Transportation Research Part c: Emerging Technologies 51, 136–148.
Vallée, J., Ecke, L., Chlond, B., Vortisch, P., 2022. Deutsches Mobilitätspanel MOP – Wissenschaftliche Begleitung und Auswertungen Bericht 2021/2022: Alltagsmobilität und Fahrleistung. https://mobilitaetspanel.ifv.kit.edu/downloads/Bericht_MOP_21_22.pdf.
Weldon, P., Morrissey, P., Brady, J., O'Mahony, M., 2016. An investigation into usage patterns of electric vehicles in Ireland. Transportation Research Part d: Transport and Environment 43, 207–225.
Wen, Y., MacKenzie, D., Keith, D.R., 2016. Modeling the charging choices of battery electric vehicle drivers by using stated preference data. Transportation Research Record: Journal of Transportation Research Board 2572, 47–55.
Wollbertus, R., Krosen, M., Van Den Hoed, R., Chorus, C., 2018. Policy effects on charging behavior of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. Transportation Research Part d: Transport and Environment 62, 283–297.
Yamamoto, T., Madre, J.L., de Lapparent, M., Collet, R., 2018. A random heaping model of annual vehicle kilometres travelled considering heterogeneous approximation in reporting. Transportation 47, 1027–1045.
Yang, Y., Yao, E., Yang, Z., Zhang, R., 2016. Modeling the charging and route choice behavior of BEV drivers. Transportation Research Part c: Emerging Technologies 65, 190–204.
Yang, M., Zhang, L., Dong, W., 2020. Economic Benefit Analysis of Charging Models Based on Differential Electric Vehicle Charging Infrastructure Subsidy Policy in China. Sustainable Cities and Society 59.
Zhang, A., Kang, J.E., Kwon, C., 2020. Multi-day scenario analysis for battery electric vehicle feasibility assessment and charging infrastructure planning. Transportation Research Part c: Emerging Technologies 111, 439–457.
Zheng, X., Menezes, F., Zheng, X., Wu, C., 2022. An empirical assessment of the impact of subsidies on EV adoption in China: A difference-in-differences approach. Transportation Research Part a: Policy and Practice 162, 121–136.
Zhongying, G., 2023. Do electric vehicle charger locations respond to the potential charging demands from multi-unit dwellings? Evidence from Los Angeles County, Transport Policy.
Zoepf, D., MacKenzie, D.K., Chernicoff, W., 2013. Charging choices and fuel displacement in a large-scale demonstration of plug-in hybrid electric vehicles. Transportation Research Record: Journal of Transportation Research Board 2385, 1–10.