The Shape of U –
On the Structure of Utility from Electric Vehicle Charging

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Abstract

With the growing adoption of electric vehicles, understanding user charging behavior is increasingly important for informing operational, investment, and policy decisions regarding their integration into the power system. While utility functions are commonly used to describe user preferences in charging behavior models, most existing studies rely on formulations with limited theoretical consistency and empirical validation, potentially leading to biased expectations. This paper empirically compares different utility function specifications and examines their implications for charging behavior modeling and charging station profitability. I introduce a novel discrete choice model framework to efficiently estimate utility function parameters from revealed preference data. Using a dataset of observed charging sessions at public charging stations in Germany, the model identifies accurate utility functions, uncovers charging preferences, and simulates station segment viability. The results suggest that charging utility is non-linear: marginal utility decreases with charged energy and marginal disutility increases with charging duration. An interaction between energy and duration leads to higher marginal valuation of energy for longer charging durations. Stations profit from inelastic demand driven by users who highly value energy content, are less price sensitive, and engage in high-value activities at the charging location, such as in urban areas or traffic hubs.

Keywords: Electric Vehicles, charging behavior, utility function, discrete choice model, revealed preference data, charging station viability

JEL classification: C25, C44, C53, Q40, R40

The contents of this paper reflect the opinions of its author only and not those of EWI.

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1. Introduction

Electric Vehcile (EV) adoption accelerates. According to IEA (2024), current stated national policies project an increase in the global Battery Electric Vehicle (BEV) stock from 28 Million in 2023 to 390 Million by 2030. Integrating the resulting electricity demand from EV charging into the power system poses a growing challenge for utilities and regulators. Even today, the challenges are becoming apparent: while infrastructure investment demand increases (IEA, 2024; McKinsey, 2022), charging stations lack profitability (Fröde et al., 2023; Hecht et al., 2022).

For decision-makers, it becomes instrumental to understand EV users' charging behavior and underlying preferences. To inform operation, investment, and policy decisions, the literature explores charging behavior models (Li et al., 2023). The models examine the demand for charging at different times and locations, allowing to form expectations about EV users' preferences. So far, the existing models must rely on simplified representations of the decision context, potentially overlooking the full empirical intricacies (Daina et al., 2017a). As a single charging decision depends on EV users' upstream and downstream travel-activity schedule, non-linearities and temporal interdependencies may occur. The temporal and spatial constraints introduce unique trade-offs that shape EV charging decisions. This work's point of departure is the explicit examination of EV users' utility structure at a public charging station.

1.1. Literature review

In the light of rising EV adoption, researchers have turned their attention to understanding the behavior of EV users. In their comprehensive review, Daina et al. (2017a) summarize the literature on EV use models, revealing two key insights. First, the existing research focuses on long-term decisions, such as EV adoption and ownership, with fewer publications addressing short-term decisions, including charging behavior. Second, among the publications on short-term decisions, only a few employ explicit choice models. Most rely on exogenous charging patterns and strategies, overlooking the dynamic and adaptive behavior of EV users. To address the gap in the literature, Daina et al. (2017a, p.458) advocates for research on "theoretical coherent modelling frameworks" and "empirical estimation and strong validation of their parameters". They further note that sparse publicly available data on EV charging poses a major challenge for achieving such real-world validation. More recently, Li et al. (2023) reviewed advancements in modeling short-term EV user choice behavior, finding that many models still depend on exogenous demand patterns. As such, the call by Daina et al. (2017a) for comprehensive frameworks and empirical validation stays mostly unanswered. Bridging the research gap requires exploring new datasets and refining models that better reflect the complexity of real-world EV charging behavior. Despite the common reliance on exogenous behavioral patterns, several publications propose utility-based models for EV user choices. A selection of utility functions, albeit often lacking theoretical or empirical grounding, is provided by Limmer (2019). Their work underscores the diversity of approaches but also highlights a recurring reliance on assumptions rather than data-driven insights, echoing concerns raised by Daina et al. (2017a).

Several publications attempt to address the gap in modeling EV user charging behavior. Table 1 summarizes the key applications of utility functions in EV charging models, highlighting their properties and data sources. A notable contribution is Daina et al. (2017b) who propose a novel joint travel-activity and charging choice model including individual characteristics and product attributes. Although they provide a seminal theoretical foundation for examining charging choices, their reliance on stated preference data and constant marginal returns limits its real-world applicability. They suggest future research to use revealed preference data for validation. In contrast, Fridgen et al. (2021) account for potential discontinuities in charging preferences by introducing a utility function depending on the state of charge (SoC) at departure and a desired departure time, but they lack empirical validation. In general, utility functions often serve as inputs for electricity demand simulations, while explicit investigation into their forms remains rare. Only Daina et al. (2017b) and Wang et al. (2021) focus directly on charging choice models. Most publications simplify by relying on a single key attribute, such as session duration or energy charged, and often assume constant marginal utility. Exceptions include Fridgen et al. (2021), Xing et al. (2021), and Daina et al. (2017b), which consider both attributes, and Fridgen et al. (2021) and Valogianni et al. (2020), which allow for more complex marginal utility structures. No choice model has yet been validated using revealed preference data. While the approaches offer valuable insights, the findings suggest an ongoing need for theoretically grounded and empirically validated consolidations of utility functions.

Table 1: Overview of utility functions used in the literature. The functions differ by marginal utility, i.e., constant (Con.), variable (Var.), and the consideration of an interaction term (Inter.). The data is either exogenously given (EX), based on stated preferences (SP), or based on revealed preferences (RP).

	Application	Marginal utility					Data		
		Time		Energy		Inter.	EX	SP	RP
Paper		Con.	Var.	Con.	Var.				
Daina et al. (2017b)	Charging choice	●		●				●	
Fridgen et al. (2021)	EV dispatch				●	●	●		
Galus et al. (2012)	Demand model			●			●		
Liu et al. (2022)	Demand model			●			●		
Nourinejad et al. (2016)	Vehicle-to-grid	●					●		
Valogianni et al. (2020)	Coordination				●		●		
Wang et al. (2021)	Charging choice			●				●	
Wu et al. (2022)	Coordination	●					●		
Xing et al. (2021)	Demand model	●		●			●		
This work (2025)	Charging choice		●		●	●			●

Simplifications in modeling charging behavior often overlook the location- and time-specific nature of user preferences. A promising foundation for improving such models can be found in the travel behavior literature, where time has long been treated as a prerequisite for consuming goods, ever since DeSerpa (1971) extended classical consumer theory. Utility can be derived from engaging in time-consuming activities, with preferences varying across locations and times (Small, 2012; Vickrey, 1973). Consequently, the rate of utility accumulation differs across locations and times (Tseng and Verhoef, 2008). While the concept is established in the travel behavior literature, refer to Bento et al. (2024) and Wichman and Cunningham (2023) for recent examples, it does not integrate energy requirements, which are central to charging decisions. Translating the logic to EV charging behavior suggests that utility functions should account for two components of user preferences: (i) the utility derived from remaining at the current location, which depends on the duration of the parking stay, and (ii) the potential utility associated with future locations, which depends both on the duration (determining the next arrival time) and the energy charged (determining the set of reachable destinations).

1.2. *Contribution*

Three observations from the literature review stand out. First, utility functions are rarely the primary object of investigation, resulting in inconsistent assumptions about their structure across publications. Second, most existing utility functions do not account for more complex preference structures, such as varying marginal utility. Third, empirical validation of the functions is limited, particularly with revealed preference data. This paper contributes to the literature by focusing on the structure of utility from EV charging. Specifically, it seeks to answer the three-part question: *Which functional form best describes the utility of charging an EV? How do utility function assumptions shape the interpretation of EV charging preferences? How do the observed utility properties relate to profitability differences between charging station segments?* To address the questions, this paper sets up a discrete choice model framework and applies it within a case study on German public charging stations. The approach yields three key contributions to the literature:

- Introducing an efficient discrete choice model to estimate charging behavior using information from revealed preference data. Curating and enriching a unique dataset on charging choices in Germany, including information on tariffs, charging curves, and EV stock.
- Proposing a utility function which (i) incorporates time and energy attributes, (ii) considers varying marginal utility, and (iii) accounts for the dependence structure between attributes. Comparing and validating the proposed utility function structures empirically.
- Examining the link between user preferences and the viability of charging station segments.

The findings show that non-linear utility functions best explain observed charging choices. Marginal utility from energy charged decreases, and marginal disutility from charging duration increases. Longer charging durations amplify the marginal utility of the energy charged. Charging stations serving inelastic demand, such as those at urban locations or at traffic hubs, achieve higher turnovers.

Section 2 presents the theoretical framework of examining charging choices. In Section 3, the empirical model is explained. Section 4 sets up the case study, before Section 5 shows the results. After discussing the findings in Section 6, the paper concludes in Section 7.

2. Discrete choice of charging an electric vehicle

Defining the choice context is fundamental to modeling decisions. This section outlines the general considerations of modeling an EV user's decision-making process at a public charging station.

2.1. Choice framework

As a starting point, Daina et al. (2017b) offer an intuitive depiction of the choice space an EV user faces when arriving at a charging station. Following their approach, Figure 1 illustrates a general choice space of EV charging options.

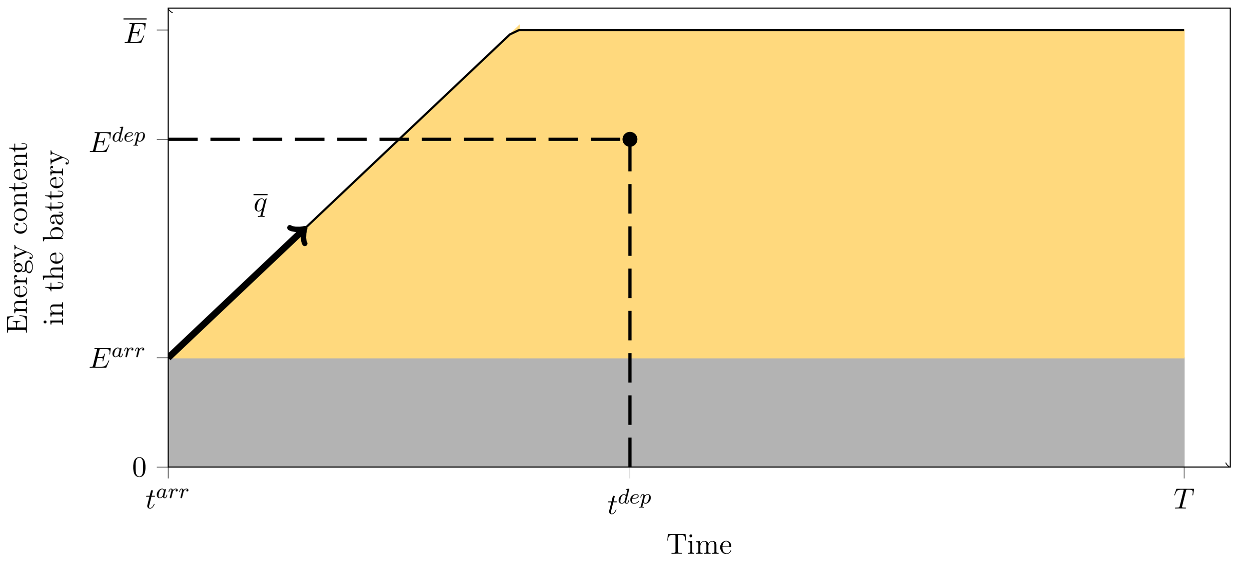

Figure 1: The choice space of an EV user arriving at a charging station from Daina et al. (2017b). The bold bullet marks the chosen alternative at departure energy E^{dep} and departure time t^{dep}. The maximum available charging rate $\overline{q}$ limits the choice space.

The main dimensions spanning the choice space are the energy content of the battery at departure from the connection point, E^{dep}, and the departure time, t^{dep}, following a total charging duration $\Delta t = t^{dep} - t^{arr}$. Both dimensions are subject to constraints. The energy content at departure is physically bounded by 0, when the battery is completely discharged, and by the battery's maximum capacity $\overline{E}$. Neglecting a vehicle-to-grid functionality, the lower bound for the energy content at departure is the energy content at arrival E^{arr}. The maximum charging rate $\overline{q}$ imposes a time-dependent upper limit on the achievable energy content at departure. Combinations of duration and energy that exceed the feasible charging rate are excluded. The time starts at arrival t^{arr}.

While the choice space is theoretically unbounded in time — an EV user could choose to stay at the charging point indefinitely — a practical upper limit is necessary for defining a finite choice set. Introducing a time horizon T effectively bounds the duration dimension. Additionally, each charging product has a certain monetary price C.

2.2. Structure of utility

The EV user selects the alternative from the choice set that maximizes their utility (Train, 2009). A critical assumption in modeling the decision is the functional form of the perceived utility from observed product attributes. As discussed in Section 1.1, most existing studies rely on utility functions that include either energy or duration, often assuming constant marginal utility. The case study compares five utility specifications. Three use linear-in-parameter forms: one depends solely on the energy content at departure (*LiP Energy*), another solely on the duration of the charging session (*LiP Duration*), and a third includes both attributes with constant marginal utility (*LiP Energy & Duration*). Building on insights from the travel behavior literature, which suggests that utility from the charging product may consist of utility gains from activities, that vary across time and location, two additional functions allow for varying marginal utility: *QiP Energy & Duration* includes quadratic terms for both attributes, while *QiP Interaction* adds an interaction term between energy and duration. The five specifications are summarized in Equation (1), with β as coefficients of the utility attributes.

$$U^D(E^{dep}, \Delta t, \beta) = \begin{cases} \beta_1 E^{dep} & \text{LiP Energy} \\ \beta_1 \Delta t & \text{LiP Duration} \\ \beta_1 E^{dep} + \beta_2 \Delta t & \text{LiP Energy \& Duration} \\ \beta_1 E^{dep} + \beta_2 \Delta t + \beta_3 {E^{dep}}^2 + \beta_4 \Delta t^2 & \text{QiP Energy \& Duration} \\ \beta_1 E^{dep} + \beta_2 \Delta t + \beta_3 {E^{dep}}^2 + \beta_4 \Delta t^2 & \text{QiP Interaction} \\ +\beta_5 E^{dep} \Delta t & \end{cases} \quad (1)$$

Figure 2 illustrates the preference structure implied by utility functions through isoquants, i.e., showing charging products with the same utility level, over a shared product space. In single-attribute utility functions, users achieve higher utility levels only by increasing one of the two attributes. The combination *LiP Energy & Duration* allows both attributes to contribute positively to the valuation of the charging product. With including quadratic terms, the utility gain from an incremental improvement in one attribute depends on the current level of that attribute. For example, the utility gain from an additional unit of energy may be higher at lower SoCs than at higher SoCs. Similarly, the interaction term captures how the marginal utility of one attribute varies with the level of the other. For instance, the utility gain from additional energy may be higher during long-duration charging sessions than during short ones.

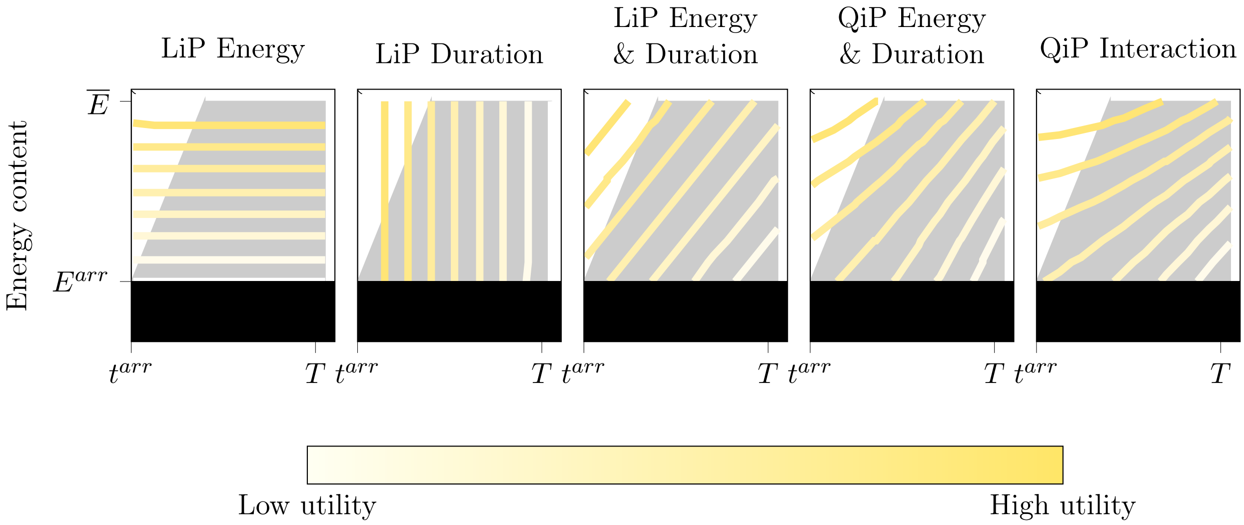

Figure 2: Isoquants of the five utility functions (in yellow), over a shared product space (in grey). The utility functions are either linear-in-parameter (LiP) or quadratic-in-parameter (QiP) and include different combinations of charging product attributes energy and duration.

The examination focuses on the direct utility function $U^D(E^{dep}, \Delta t, \beta)$, which depends on energy content and charging duration. To account for the costs C of charging products, the nominal indirect utility function is expressed as $U^N(E^{dep}, \Delta t, C, \beta, \gamma)$ in equation (2), with γ as coefficient of the product costs.

$$U^N(E^{dep}, \Delta t, C, \beta, \gamma) = U^D(E^{dep}, \Delta t, \beta) + \gamma C \tag{2}$$

3. Empirical model

Against the background of the decision framework presented in Section 2, this section presents an empirical model that allows to estimate the coefficients of different utility functions.

3.1. Discrete choice model estimation

This paper employs a discrete choice framework to efficiently estimate the coefficients β and γ in the nominal utility functions. Discrete choice models are rooted in the principle of utility-maximizing behavior by decision-makers (Train, 2009). The concept of *random utility* provides a useful bridge between the theoretical behavior and the practical limitations of observing only a part of the decision context and the resulting choices (Berbeglia et al., 2022).

The decision maker of charging event s in all charging events S derives a utility $U^R_{s,j}$ from each product j in the choice set J and selects the alternative i that yields the highest utility, i.e., $U^R_{s,i} > U^R_{s,j} \; \forall \; j \; in \; J$ (Train, 2009). While the decision-maker's utility is unobservable, the attributes of the products and the user's characteristics are. The observable charging product attributes are energy content at departure $E^{dep}_{s,j}$, charging duration $\Delta t_{s,j}$, and cost $C_{s,j}$. Based on the attributes, a nominal utility function $U^N_{s,j}(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j}, \beta, \gamma)$ can be specified (Train, 2009). To account for unobserved factors, the random utility $U^R_{s,j}$ is decomposed into nominal utility $U^N_{s,j}$ and an error term $\epsilon_{s,j}$ as shown in equation (3) (Berbeglia et al., 2022).

$$U^R_{s,j} = U^N_{s,j}(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j}, \beta, \gamma) + \epsilon_{s,j} \tag{3}$$

The error terms $\epsilon_{s,j}$ are unknown to the researcher and treated as random (Train, 2009). By specifying the joint density distribution of the random factors, the researcher can model the probabilistic assumptions about the decision maker's choice behavior. Various discrete choice models arise from different assumptions about the joint density distribution (Berbeglia et al., 2022). The choice model determines the choice probability assigned to every alternative in the choice set. The multinomial logit (MNL) and the mixed multinomial logit model (MMNL) are among the most common (Berbeglia et al., 2022).

In the MNL model, the probability that an EV user chooses alternative j, $\mathcal{P}(j|J)$, is defined in equation (4a). The MMNL model allows unobserved factors to follow any distribution, making it fully general (Train, 2009). Unlike the MNL model, which estimates point values for the utility function coefficients β, the MMNL estimates the parameters θ of a density function $f(u^N|\theta)$ for the coefficients. The flexibility enables the model to account for variation in preferences across EV users or different market segments. Equation (4b) defines the probability of choosing an alternative j in the MMNL model, where any density function can be assumed for f.

$$\mathcal{P}(j|J) = \frac{e^{U_j^N}}{\sum_{i \in J} e^{U_i^N}} \tag{4a}$$

$$\mathcal{P}(j|J) = \int \frac{e^{u_j^N}}{\sum_{i \in S} e^{u_i^N}} f(u^N|\theta) du^N \tag{4b}$$

The estimation process seeks to identify the model specification that best explains a given in-sample set of observed charging choices. The process involves estimating the coefficients β for the MNL model or the distribution parameters θ for the MMNL model, alongside the cost coefficient γ. Equation (5) presents the likelihood function for a given utility functional form $\mathcal{U}$ (e.g., *LiP Energy* or *QiP Interaction*) within a discrete choice model $\mathcal{M}$ (e.g., MNL or MMNL). The likelihood is calculated by the product of probabilities for all observed charging events s in the in-sample dataset S^{in}.

$$\mathcal{L}_{\mathcal{U},\mathcal{M}} = \prod_{s}^{S^{in}} \mathcal{P}_{\mathcal{U},\mathcal{M}}(j_s^o | J_s, \beta_{\mathcal{U},\mathcal{M}}, \theta_{\mathcal{U},\mathcal{M}}, \gamma_{\mathcal{U},\mathcal{M}}) \tag{5}$$

The coefficients ($\beta_{\mathcal{U},\mathcal{M}}$, $\gamma_{\mathcal{U},\mathcal{M}}$) and parameters ($\theta_{\mathcal{U},\mathcal{M}}$) are estimated by maximizing the log-likelihood function, as defined in equation (6).

$$\max_{\beta,\gamma,\theta} \sum_{s}^{S^{in}} \log \mathcal{P}_{\mathcal{U},\mathcal{M}}(j_s^o | J_s, \beta_{\mathcal{U},\mathcal{M}}, \theta_{\mathcal{U},\mathcal{M}}, \gamma_{\mathcal{U},\mathcal{M}}) \tag{6}$$

3.2. Metrics

The first question of this paper seeks the utility function that best models observed charging choices. For assessing the actual utility function fit, the Root Mean Square Error (RMSE) as the evaluation metric is applied to an *out-of-sample* set S^{out} of charging session observations, as shown in equation (7). The RMSE is a common measure to compare the model computations with real observed values

(Berbeglia et al., 2022), reducing the effect of potential overfitting by increasing model complexity.

$$RMSE(S^{out}, \mathcal{P}_{\mathcal{U},\mathcal{M}}) = \sqrt{\frac{\sum_s^{S^{out}} \sum_j^{J_s} (I(j = j_s^o) - \mathcal{P}_{\mathcal{M}}(j|J_s))^2}{\sum_s^{S^{out}} (|J_s| + 1)}} \tag{7}$$

The second question examines the implied preferences of utility function assumptions. In discrete choice models, coefficient magnitudes are often not directly interpretable because the dependent variable represents an abstract utility that determines choice probabilities. A common approach to illustrate the implications of estimated coefficients is to examine trade-offs between product attributes and costs. Following Bierlaire (2017), such trade-offs can be derived by identifying changes in attribute levels that compensate for cost increases, such that $U^{dep}_{s,j}(C_{s,j}+\delta^C_{s,j}, X_{s,j}+\delta^X_{s,j}) = U^{dep}_{s,j}(C_{s,j}, X_{s,j})$. The travel behavior literature typically examines the *value of time* (Bierlaire, 2017; Train, 2009). This paper extends the examination by calculating the *value of energy*. The *value of time* for the utility functions *LiP Energy & Duration* and *QiP Interaction* is computed using equation (8), while the *value of energy* is derived from equation (9).

$$VoT = \frac{\delta^C_{s,j}}{\delta^{\Delta t}_{s,j}} = \frac{(\delta U^N_{s,j}/\delta\Delta t_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})}{(\delta U^N_{s,j}/\delta\Delta C_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})} = \begin{cases} \frac{\beta_2}{\gamma} & \text{LiP Energy \&Duration} \\ \frac{\beta_2+2\beta_4\Delta t_{s,j}+\beta_5 E^{dep}_{s,j}}{\gamma} & \text{QiP Interaction} \end{cases} \tag{8}$$

$$VoE = \frac{\delta^C_{s,j}}{\delta^{E}_{s,j}} = \frac{(\delta U^N_{s,j}/\delta E^{dep}_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})}{(\delta U^N_{s,j}/\delta\Delta C_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})} = \begin{cases} \frac{\beta_1}{\gamma} & \text{LiP Energy \&Duration} \\ \frac{\beta_1+2\beta_3 E^{dep}_{s,j}+\beta_5\Delta t_{s,j}}{\gamma} & \text{QiP Interaction} \end{cases} \tag{9}$$

The third question links EV user preferences to charging station profitability, indicated by total turnover. The total turnover per charging station m can be obtained by summing over all weighted charging products in the choice sets J_s of the charging sessions S^m, as shown in equation (10). For each station, the results are scaled with the weight of the samples in the in-sample set in relation to the total number of session in the entire dataset.

$$R^{Total}_m = \sum_s^{S^m} \sum_j^{J_s} P(j|J_s) C_{s,j} \tag{10}$$

4. Case study

In the case study, the efficiency of the proposed model approach is demonstrated by applying it to a curated revealed preference dataset of charging sessions at public charging stations in Germany.

4.1. Data

The primary data source is the *Online Reporting Charging Infrastructure* provided by the German National Centre for Charging Infrastructure (NCfCI) (NCfCI, 2024). Publicly accessible charging stations are eligible for German charging infrastructure founding programs. Program beneficiaries must report all charging sessions conducted at the funded station for six consecutive years following their installation. The reports form the basis of the dataset used in this study.

The key indicators taken from the session data are the date and time of arrival, the duration of connection, the charged energy, a location activity parameter, an area type parameter, and the charging station's connection points and their power (NCfCI, 2024). Connection duration is initially recorded in seconds but is discretized into hourly steps to enhance computational traceability. The case study distinguishes three segmentations, *Area*, *Activity*, and *Charger*. Area types are categorized based on German spatial observations from BBSR (2023). The location activity parameter provides qualitative information about the charging station's setting, such as whether it is located in a public parking lot, a customer parking area, or near a federal highway. The *Charger* segmentation distinguishes *AC* and *DC* charging depending on the connection point power. Appendix B.1 describes the segmentations and their assignment rules. Additionally, the case study distinguishes two time segmentations, one by type of day and one by time of day, to examine time-dependent preferences. Day types are *weekdays* and *weekends*. Following Federal Statistical Office of Germany (2024), three time periods are defined: *23-07*, capturing the night, where most people spend their time at home sleeping; *08-16* as day period during which the main activity is work; and *17-22*, capturing the evening, during which people mainly leisure activities.

The dataset covers the years 2018-2023, encompassing a total of 21.1 Mio. observed charging sessions at 13,410 public charging stations. Given the extensive data volume, a pre-selection of charging sessions is necessary for the empirical analysis. To avoid potential biases from the COVID-19 pandemic and the European energy crisis, only the most recent charging sessions reported in

2023 are considered, resulting in 7.96 million sessions. The primary objective of the analysis is to distinguish different forms of utility derived from EV-charging. To capture relative preferences effectively, the choice set must offer various distinct alternatives. The case study focuses on 1,145 charging stations with at least two connection points of differing power levels, yielding 1.03 million charging sessions. To keep the estimation computational tractable, a random sample of 10,000 sessions is selected, with 8,000 used as an in-sample set and 2,000 reserved for out-of-sample RMSE evaluation. To elaborate on the sample size, Appendix C.1 presents sensitivities of the model results on the number of observations and the number of alternatives included in the choice set. Appendix C.2 explores sensitivities on the pre-selection of the observations included in the in-sample set.

The revealed preference data collected from charging station operators does not include information on specific choice circumstances, such as the applicable charging tariff or the battery's SoC upon arrival, nor on individual user characteristics, such as socio-economic factors or exact travel-activity schedules. Enriching the dataset with additional assumptions and supplementary information allows for an approximation of the specific choice circumstances. Key parameters for designing the choice set that are unobserved include the battery capacity $\overline{E}_s$ of the EV, the energy content in the battery at arrival E_s^{arr}, the time horizon of the choice T_s, and the costs of the charging products $C_{s,j}$. Although individual user characteristics cannot be directly accounted for, the MMNL model accommodates variation in coefficients across the dataset, thereby capturing a broader range of preference structures. Appendix B.2 describes in detail the imputations performed to enrich and curate the data for the case study. Table 2 summarizes the key assumptions made.

4.2. Choice set

The actual choice set of available charging products is not directly observable because the data originates from revealed preferences instead of stated preferences. Constructing a realistic representation of the choice set is pivotal to the reliability and accuracy of the discrete choice model's results. While EV users could theoretically select any combination of energy and duration within the defined choice space outlined in Section 2.1, practical constraints at public charging stations restrict the actual choices observed in the case study dataset. The derivation of this paper's choice

Table 2: Assumptions used for the creation of choice sets and choices.

Parameter	Symbol	Unit	Value	Source
AC adhoc charging price	P^{AC}	€/kWh	0.58	EC (2024)
DC adhoc charging price	P^{DC}	€/kWh	0.72	EC (2024)
Maximum free blocking time	$\underline{t}^{Block}$	h	4	Appendix B.5
Blocking fee	P^{Block}	€/min	0.1	Appendix B.5
Maximum paid blocking time	$\bar{t}^{Block}$	€	12	Appendix B.5
Charging losses		%	15	ADAC (2022)
Minimum state of charge at arrival	$\underline{E}^{arr}$	%	10	Own assumption
Time resolution	δt	min	60	Own assumption

set relies on three key assumptions. First, the EV user maintains a constant charging rate throughout the session. Switching rates would require disconnecting and reconnecting, which is treated as departure from the charging point. Only energy-duration combinations achievable with a single charging rate are included. Second, charging terminates either when the battery reaches its maximum capacity or when the user departs. The choice set excludes combinations where charging stops at a specific target energy content, as interruption is only possible through departure. Finally, users cannot connect to a charging point without starting to charge. While they may remain parked after the battery is fully charged, the choice set assumes that charging always commences upon connection. Figure 3 illustrates the choice set considering the limits of the observed choices in the case study dataset.

The choice set must consist of discrete, unique options, requiring the two continuous dimensions — energy and time — to be discretized. To achieve the discretization, all energy-duration combinations are sampled at a time resolution of δt, with each combination mapped to its corresponding energy content at departure. The discretization results in a finite choice set, J_s, containing all available charging products j available for the EV user at the charging event s. Each charging product is defined by three primary attributes: the energy content in the battery at departure $E^{dep}_{s,j}$, the session duration $\Delta t_{s,j}$, and the associated cost of the charging session $C_{s,j}$. The structured choice set ensures that the EV user's options are clearly defined and amenable to discrete choice modeling. Each choice set includes a no-charge option $j = 0$ representing departure with the energy content of arrival with no duration and no cost. Random utility models only capture the differences in utility

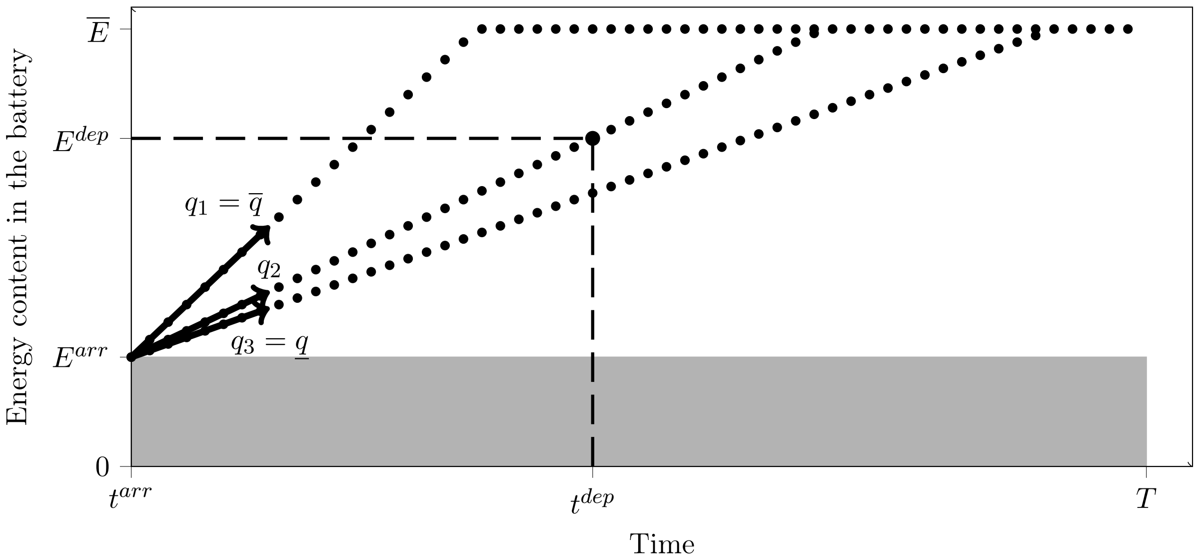

Figure 3: The discrete choice set of an EV user arriving at a charging station based on Daina et al. (2017b). The bullets mark alternatives in the choice set, with the bold bullet marking the chosen alternative at departure energy E^{dep} and departure time t^{dep}. The set of available charging rates Q consists of the three rates q_1, q_2, and q_3, with q_1 being the maximum and q_3 the minimum. $\overline{E}$ is the battery's capacity and T the time horizon.

between different alternatives (Train, 2009, p.24). Following the normalization in Berbeglia et al. (2022), the nominal utility of the no-charge option $j = 0$ with the lowest arrival energy content $\min_{s \in S} E^{arr}$ is set to zero, as expressed in equation (11).

$$U^N_{s,0}(\min_{s \in S} E^{arr}, 0, 0, \beta, \gamma) = 0 \tag{11}$$

4.3. Choice and station description

By constructing the choice sets according to the approach described in Section 4.2, each observation is associated with a set of available charging products at the time of arrival, as well as the product that was actually chosen. For the total set of actual choices, Figure 4 depicts the distribution of the three product attributes charged energy, duration, and price paid.

On average, an EV user pays 14,5 € for leaving the charging station after 1.2 hours with 63 kWh. The dataset exhibits right-skewed distributions, characterized by numerous small to medium values and a few large ones. The tail is particularly pronounced for the energy charged and the total price paid. There are only a few observations of EVs leaving the charging station with a fully charged 120 kWh battery, paying more than 70 € for the charging session. On the other hand, the majority

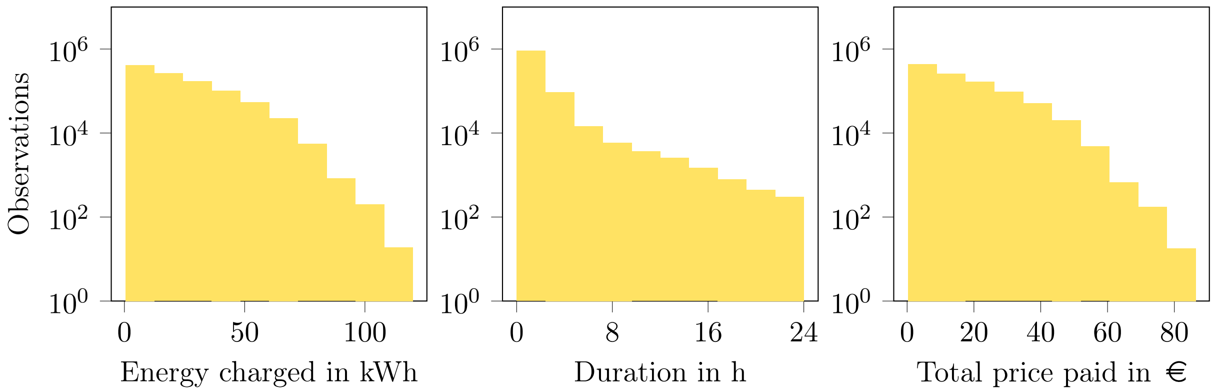

Figure 4: The distribution of the energy charged, duration, and total price paid of the chosen products in the dataset of 1.03 mio. charging sessions reported for 2023 at 1,145 charging stations with varying charging rates based on (NCfCI, 2024) and the assumptions in 4.1.

charges up to 50 kWh, paying in total up to 40 €. For the duration, the tail exists, although it is less strong. Notably, a consistently significant share of sessions lasts longer than 8 hours, though the majority charges for less than 4 hours.

Each charging session occurs at a specific connection point associated with a particular charging station. Given that the dataset encompasses all reported sessions for publicly funded charging stations, it provides valuable insights into the stations' key economic characteristics. Figure 5 presents the distribution of absolute turnover, derived from the charging session data and underlying assumptions, across the entire set of charging stations. The charging session distributions translate into a right-skewed distribution of charging station's turnover. Most of the charging stations generate an income of up to 20,000 € with fewer stations generating more than 50,000 €. Only a few outliers report turnovers beyond 100,000 €.

5. Results

The discrete choice model is implemented in biogeme (Bierlaire, 2024). The computation of the segmented coefficients follows Bierlaire and Ortelli (2023). Applied to the case study, the model allows comparing utility functions, assessing their implications, and evaluating the turnover of the corresponding charging stations.

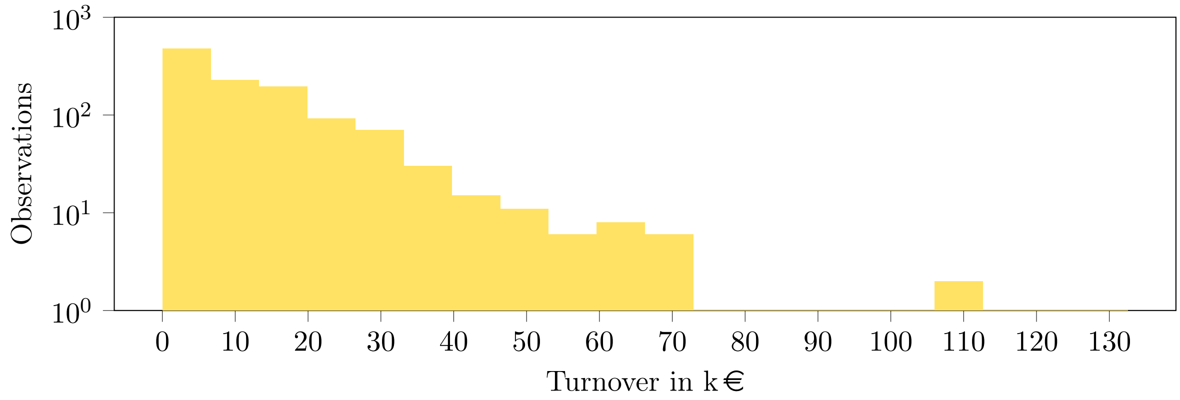

Figure 5: The distribution of the total turnover in 2023 at 1,145 charging stations with varying charging rates based on (NCfCI, 2024) and the assumption in 4.1.

5.1. Utility function comparison by model-fit

To answer the first question, the coefficients of each of the five utility functions from Section 2.2 are fitted to the in-sample set and evaluated against the out-of-sample set. For each utility function, two discrete choice models are fitted: an MNL and an MMNL with normal distributed coefficients. Figure 6 illustrates the RMSE of the models applied to the out-of-sample set.

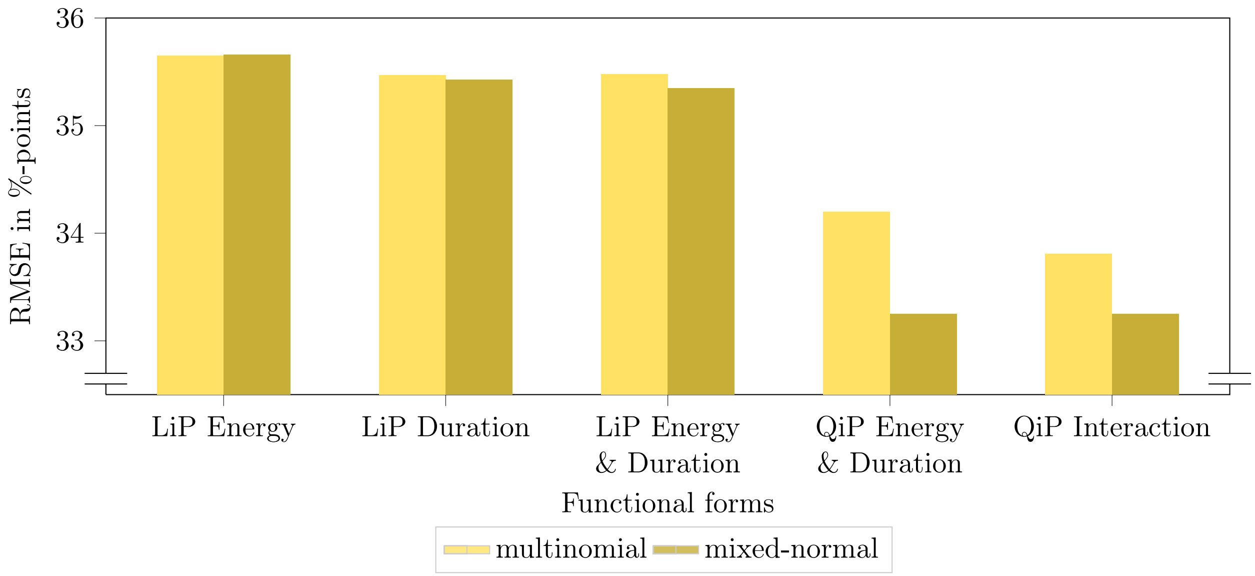

Figure 6: The Root Mean Square Error of the five utility functions under a multinomial logit and a mixed multinomial logit discrete choice model. The RMSE is computed on an out-of-sample dataset of 2,000 observations.

The RMSEs indicate that a two-parameter utility function based on duration and price slightly outperforms one based on energy content at departure and price. Duration may be a stronger explanatory variable for two reasons. First, because of the limited battery capacity compared to a broader time horizon, duration choices exhibit a greater variability than energy choices. Second, time constraints likely weigh more heavily in user decisions than energy needs. Accordingly, utility functions including duration capture more variation in product choices. Including both energy and duration yields a model of comparable performance, in the MNL case and slightly improved fit in the MMNL case, suggesting that while connection time explains much of the observed behavior, energy content contributes significantly.

The linear-in-parameter utility function including energy content at departure, connection duration, and price offers a natural starting point for modeling charging decisions at public charging stations. As argued in Section 2.2, it may not fully reflect an EV user's decision rational. The observed reduction in RMSE when introducing quadratic terms for energy and duration in *QiP Energy & Duration* suggests that marginal utility is not constant, but instead increases or decreases with the attribute level. Incorporating an interaction term between energy and duration further improves the model fit, indicating that the marginal utility of one attribute depends on the level of the other, e.g., the value of a given energy level depends on the time required to achieve it, and vice versa. To illuminate the non-linear relationships, the Section 5.2 presents the estimated coefficients.

The MNL and the MMNL with normal distributed coefficients yield the same ranking of utility functions. Overall, the MMNL choice model outperforms the MNL choice model, with performance differences increasing alongside model complexity. The significant difference suggests the presence of preference heterogeneity in the observed choices, which is better captured by a distribution of coefficients than by fixed estimates. The heterogeneity may stem from individual differences or other contextual factors such as time of day. Section 5.5 further investigates the heterogeneous effects by examining different charging station segments and times of day. The MNL model is used for further analysis, as it is computationally more tractable and reveals the same underlying utility structures as the MMNL model.

5.2. Utility function comparison by estimated coefficients

Examining the actual coefficients of the estimated utility functions answers the second research question of this paper. The model improvement by incorporating parameters allowing for non-linear forms of utility in Section 5.1 suggests that the quadratic and interaction terms explain some share of the variation in the observed charging choices. Table 3 lists the estimated coefficients for each of the five utility function specifications under the MNL model.

Table 3: The estimated coefficients of the multinomial logit model for the five utility functions.

	(1)	(2)	(3)	(4)	(5)
	LiP Energy	LiP Duration	LiP Energy & Duration	QiP Energy & Duration	QiP Interaction
Costs	-0.064***	0.011***	-0.050***	-0.052***	-0.056***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.004)
Energy	0.046***		0.056***	0.384***	0.498***
	(0.002)		(0.002)	(0.008)	(0.011)
Duration		-0.226***	-0.248***	-0.008	-1.238***
		(0.008)	(0.009)	(0.021)	(0.086)
Energy^2				-0.003***	-0.004***
				(0.000)	(0.000)
Duration^2				-0.019***	-0.052***
				(0.004)	(0.006)
Interaction					0.020***
					(0.001)

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

The cost of a certain charging product shows for four of the five utility functions a negative sign, significant at the 1% level. The negative coefficient intuitively associates higher prices with a lower product choice probability. Only in the linear-in-parameter utility function including the energy costs and the duration in column (2), the sign is positive. The counterintuitive positive sign in contrast to the other utility functions hints at a potential incomplete specification by only using costs and charging duration to explain charging choices. Omitting the energy content variable may lead to a positive cost sign, compensating the missing positive effect of energy content in the battery.

The sign of energy content in the battery at departure is positive in all four utility functions where it is included and significant at the 1% level. As can be expected from the literature, higher levels of energy charged are associated with higher levels of utility (Daina et al., 2017b). The negative sign of the quadratic term, significant at the 1% level, suggests that the positive marginal utility from energy content in the battery is diminishing. On average, with higher levels of energy content, the utility from one additional unit of energy stored in the battery decreases. The resulting utility function is concave in the charging product's attribute energy, consistent with consumer theory.

The connection duration at the charging station has a negative sign, significant at the 1% level, except for *QiP Energy & Duration*. The negative sign suggests that a longer connection duration creates disutility for the EV user. Given that all other attributes are equal, the user would prefer a charging product with a shorter duration over a product with a longer one. The sign of the quadratic term is negative, indicating that the marginal disutility decreases with a longer connection duration. It is significant at the 1% level. While the positive marginal utility from energy diminishes, the disutility from duration increases. The longer the charging takes, the higher is the marginal disutility from additional time of parking at the charging station. The utility function is convex in the charging product's attribute duration.

The fifth utility function in column (5) includes, beside the linear and quadratic terms of energy and duration, an interaction term between energy content in the battery at departure and the duration of the charging session. The interaction term's sign is positive and significant at the 1% level. A positive interaction term between energy and duration suggests that the marginal utility from an additional unit of energy stored in the battery increases in the duration of the connection time. The higher the charging duration, the higher the loss in utility of foregone energy. Put into different words, the positive interaction term suggests that marginal disutility from duration is higher at low levels of energy than at high levels of energy.

For the model results presented in column (5), statistical properties of the specification and the robustness of the results are discussed in Appendix C. Appendix C.3 explores potential model extensions using specific constants, while Appendix C.4 investigates the correlation between the higher-order utility function variables.

5.3. The value of time and energy

The value of time and energy may provide clearer insights into the underlying preferences of EV users than estimated coefficients alone. Figure 7 illustrates both values for the utility functions *LiP Energy & Duration* and *QiP Interaction.* Because the marginal utilities of the quadratic utility function depend on the battery's energy content and the charging duration, the values are shown for several attribute levels.

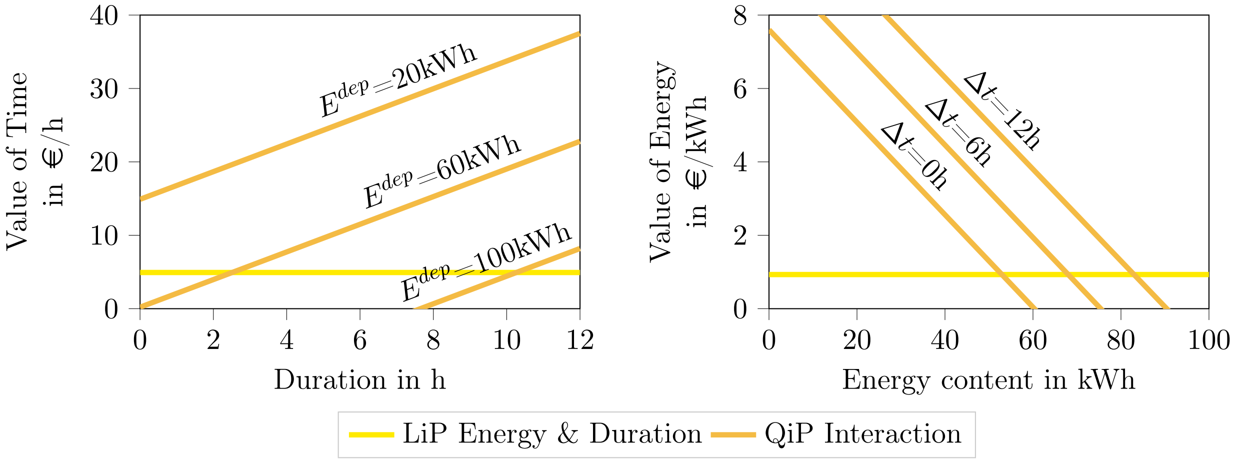

Figure 7: The value of time over the duration of the charging product and the value of energy over the energy content in the battery at departure for the utility functions *LiP Energy & Duration* and *QiP Interaction.*

Under the linear utility function, time has a value of 5 €/h, while under the quadratic utility function with interaction term, the value of time ranges from -14 €/h at 0 h and 100 kWh up to 38 €/h at 12 h and 20 kWh depending on the actual energy content in the battery and the charging duration. In contrast to the positive values, indicating that users are willing to pay to leave the charging station earlier, negative values suggest a willingness to pay for staying longer. As outlined in Section 1.1, the utility functions reflect both the utility gained from time spent at the current location and the potential utility of time at future locations, which are reachable with the charged energy. A positive value of time implies that the utility at future locations exceeds that at the current one, whereas a negative value indicates the opposite. Such negative values may arise from instances where EV users remain connected longer than necessary to fully charge, reflecting a preference for staying at the current location.

The value of time reflects the increasing marginal disutility from duration, it increases by 2.1 €/h per hour. The increase with duration suggests that, over time, utility at the current location diminishes while the potential utility at future locations increases, resulting in a higher willingness to pay for earlier departure. Similarly, the positive interaction term implies that the time-dependent value of time decreases as energy content increases. At lower energy levels, the value of time is higher, indicating greater time sensitivity among EV users with insufficient charge. The sensitivity suggests that users anticipate the time required to reach a sufficient charge and exhibit a stronger preference for faster charging when energy levels are low.

The value of energy under a linear utility function is 0.94 €/kWh. Under the quadratic utility function with interaction term, it ranges from -4.96 €/kWh at 0 h and 100 kWh to 11.34 €/kWh at 12 h and 0 kWh. A positive value indicates a willingness to pay for additional energy content, while a negative value suggests a willingness to pay for less. The willingness to pay for less energy at the same duration may hint at the EV user's expectation about future trips and charging options. If the current energy level is sufficient to reach the next destination, and cheaper charging is expected elsewhere, users may prefer to limit charging at the current location, even at a cost.

The diminishing marginal returns are reflected in the decrease in the value of energy by 12.6 ct/kWh per additional kWh of energy stored in the battery. The decrease in the value of energy illustrates that there may be a saturation effect of energy charged once the energy required to reach the next location is charged. Similar to the value of time, the positive interaction term reveals that the value of energy increases with longer durations. The longer the charging duration, the higher is the willingness to pay for energy, reflecting users' preference to make productive use of the connection time.

The value of energy and time demonstrate that the *QiP Interaction* utility function accounts for the charging preference variation with duration and the energy level. In contrast, the *LiP Energy & Duration* function assumes constant values of time and energy. Section 5.5 further explores preference heterogeneity by examining different charging station segments and times.

5.4. Coefficient differences between charging station segments

To answer the third research question, the coefficients can be distinguished by charging station segment. In the assessment of charging choices, the spatial and temporal circumstances play a significant role. A segmentation may allow identifying differences between charging station categories. The MNL model with the utility function *QiD Interaction* is estimated for three different spatial segmentations, i.e., *area*, *activity*, and *charger*, and two temporal segmentations, *day* and *time of day*. Table 4 and 5 show the resulting coefficients.

Table 4: Estimated coefficients of the multinomial logit model for the utility function *QiD Interaction* with quadratic and interaction terms. The results include coefficients of three spatial segmentations, *Area*, *Activity*, and *Charger*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Area			Activity		Charger	
	Rural	Sub-Urban	Urban	Parking	Refueling	AC	DC
Costs	-0.062***	-0.057***	-0.050***	-0.052***	-0.110***	-0.055***	-0.075***
	(0.009)	(0.019)	(0.019)	(0.004)	(0.015)	(0.008)	(0.016)
Energy	0.567***	0.502***	0.462***	0.463***	0.822***	0.341***	0.532***
	(0.029)	(0.060)	(0.062)	(0.011)	(0.051)	(0.024)	(0.049)
Duration	-1.513***	-1.249***	-1.041**	-1.104***	-2.806***	-0.301**	-1.395***
	(0.223)	(0.462)	(0.472)	(0.088)	(0.456)	(0.131)	(0.285)
Energy^2	-0.005***	-0.004***	-0.004***	-0.004***	-0.006***	-0.003***	-0.004***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Duration^2	-0.009	-0.056**	-0.068***	-0.060***	0.002	-0.103***	-0.052***
	(0.010)	(0.022)	(0.023)	(0.006)	(0.028)	(0.008)	(0.020)
Interaction	0.020***	0.021***	0.019***	0.019***	0.035***	0.018***	0.018***
	(0.004)	(0.007)	(0.008)	(0.001)	(0.007)	(0.002)	(0.005)
Observations	1193	4459	2348	7012	988	2673	5327

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

The three segmentations reveal variation in the magnitude of the negative cost coefficient, indicating differing sensitivities to prices across segments. A larger absolute coefficient suggests greater price sensitivity, which may arise from two factors: (i) tighter budget constraints among users, and (ii), the availability of competitive charging alternatives downstream of the user's travel-activity schedule. In the *area* segmentation, rural stations show a more negative cost coefficient than urban ones, suggesting greater price sensitivity among rural users. The difference may reflect the rural-urban income gap and greater access to alternative, often cheaper, private charging options in rural areas. Although urban areas feature denser public charging infrastructure and meshed road networks, high demand and limited flexibility in travel routes may reduce the effective availability of substitutes. Additionally, the cost differences between public charging options in urban areas may be smaller than the price gap between public and private charging in rural areas. Similarly, the greater cost sensitivity observed for refueling in the *Activity* segmentation and for DC charging in the *Charger* segmentation further supports the role of accessible alternatives. Refueling stations are often located at traffic hubs such as petrol station on federal highways (see Appendix B.1), where multiple downstream charging options are available.

Differences in the magnitude of the linear energy coefficient may be explained by the EV users' anticipated energy needs for upcoming trips in their travel-activity schedule. When additional charging is not critical, e.g., for short upcoming trips or when the arrival energy level is already sufficient, users tend to show lower preferences for energy. Differences in the quadratic coefficient, in turn, capture how sharply the marginal utility of energy diminishes once a sufficient level is reached. Higher absolute values suggest a stronger saturation effect, meaning that energy beyond the amount required for the next trip holds considerably less value. Compared to parking, the magnitude of the linear energy coefficient in the refueling segment is significantly higher, suggesting that EV users place greater value on energy at refueling locations. The higher valuation likely reflects longer anticipated travel distances, e.g., along federal highways, and the associated energy needs, while upcoming trips from parking locations may be shorter. The higher magnitude of the quadratic energy coefficient at refueling stations suggests a steeper decline in marginal utility once sufficient energy is charged. The observation could imply that EV user at refueling stations are more aware of upcoming energy requirements. In the *area* segmentation, EV users at *rural* stations exhibit a higher valuation of energy, which may be attributed to generally longer distances between destinations in rural compared to urban areas.

The underlying trade-off between utility gained at the current charging location and utility at subsequent locations, described in Section 1.1, may explain the variation in the duration coefficients across segments. A high magnitude of the negative linear duration coefficient suggests that users perceive low utility at the current location relative to future ones. The greater the negative coefficient, the larger the gap in perceived utility between staying and leaving. Similarly, a high negative quadratic duration coefficient may reflect rigid travel-activity schedules, where utility declines rapidly with longer stays and increases sharply at the next stop. Lower magnitudes, by contrast, indicate more flexible schedules and smoother transitions.

In the *area* segmentation, rural stations exhibit a more negative linear duration coefficient, suggesting that users derive less utility from staying in rural locations. The magnitude of the quadratic duration coefficient is higher in urban areas, implying tighter scheduling constraints and a stronger aversion to extending stays beyond a planned departure. In rural areas, the quadratic duration coefficient is even insignificant, supporting the interpretation of more flexible travel-activity schedules. EV users experience particularly high disutility from time spent at refueling locations, with a coefficient of -2.806. The insignificant quadratic term suggests that users avoid time at refueling stations from the start. The primary motive for stopping is to charge, not to engage in other activities. In contrast, at parking locations, e.g., customer parking lots (see Appendix B.1), the magnitude of the linear duration coefficient is lower, indicating that users initially derive utility from the location. Once their activities conclude, the preference to leave increases, as reflected in the more negative quadratic coefficient. In these cases, charging may be more opportunistic or secondary. Differences between AC and DC chargers show a similar pattern, albeit less pronounced. The similarity may be linked to the installation context: AC chargers are more commonly found at parking locations, while DC chargers are more often installed at refueling stations.

The interaction term captures how strongly the attributes of energy and duration complement each other in users' utility evaluations. A high coefficient indicates, that one attributes's impact on the valuation of the other attribute is high, while a low coefficient rather indicates independence in EV users' valuation. Across most segments, the interaction coefficient varies only slightly. Only the segment refueling shows a significantly higher coefficient of 0.035. The high value reinforces the interpretation that the primary purpose of stopping at refueling stations is to charge the battery. Here, users judge the value of time spent by how much energy is charged during that time—and vice versa, they assess the value of the charged energy in light of how long the process takes.

Segmenting the observations by *day* and *time of day* reveals the time dependency of EV users' charging preferences. The higher values indicate greater price sensitivity during leisure times, possibly because users anticipate more convenient or lower-cost charging opportunities later downstream in their travel-activity schedule, such as charging at home. Cost sensitivity is lowest at night, between

Table 5: Estimated coefficients of the multinomial logit model for the utility function *QiD Interaction* with quadratic and interaction terms. The results include coefficients of two temporal segmentations, *Day* and *Time of day*.

	(1)	(2)	(3)	(4)	(5)
	Day		Time of day		
	Weekday	Weekend	23-07	08-16	17-22
Costs	-0.054***	-0.061***	-0.035***	-0.056***	-0.061***
	(0.004)	(0.011)	(0.010)	(0.021)	(0.021)
Energy	0.490***	0.517***	0.430***	0.489***	0.536***
	(0.013)	(0.033)	(0.034)	(0.070)	(0.072)
Duration	-1.298***	-1.055***	-1.137***	-1.039*	-1.611***
	(0.103)	(0.260)	(0.267)	(0.546)	(0.557)
Energy^2	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Duration^2	-0.054***	-0.051***	-0.042***	-0.073**	-0.033
	(0.006)	(0.019)	(0.014)	(0.029)	(0.030)
Interaction	0.022***	0.017***	0.020***	0.019**	0.024**
	(0.002)	(0.004)	(0.004)	(0.009)	(0.009)
Observations	5739	2261	763	4605	2632

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

from 23:00 and 07:00, suggesting that users are less inclined to delay or substitute charging, likely due to limited future alternatives during nighttime.

The energy coefficient is highest on weekends and in the evening, indicating that users anticipate longer upcoming trips, e.g., for distant leisure activities, or prefer to start the next day with a sufficiently charged battery. In contrast, the coefficient is lower at night and in the early morning, suggesting that shorter trips are expected or energy levels at arrival are already adequate. The quadratic energy coefficient remains stable across all time segments, implying that the degree of diminishing marginal utility for energy, beyond the level needed for upcoming trips, is largely constant over time.

The magnitude of the negative linear duration coefficient is highest in the evening, suggesting that the utility of staying at the charging station is considerably lower than the utility of proceeding to the next activity, likely related to leisure after the workday. The insignificant quadratic term supports the interpretation that disutility arises immediately, with little tolerance for extended stays. On average, the primary purpose of the stop may be charging. On weekends and during daytime hours (08:00–16:00), the lower magnitudes of the linear coefficient suggest higher utility at the charging location itself. Weekend stays may coincide with longer leisure activities, while daytime charging often overlaps with structured routines such as work, reducing sensitivity to duration. Notably, the quadratic coefficient is relatively high during the day, indicating more rigid transitions between scheduled activities, for instance, a strong preference to leave once work is over. The interaction term varies less across time than across station segments. It is slightly higher in the evening, indicating that stops during are more strongly driven by the need to charge the EV rather than by activities at the location. In contrast, the lower magnitude on weekends suggests that charging events are more optional, with weaker interdependence between energy and duration in users' preferences.

5.5. Turnover by charging station segment

Decision margins quantify how choice probabilities shift in response to variations in product attributes, given a parameterized utility function and a defined choice set. Two margins illustrate the estimated utility functions effect on the turnover of a charging station: a change in the energy content at arrival and a change in the energy price, as illustrated in Figure 8.

Variations in energy content at arrival indicate how responsive charging station usage is to the availability of prior charging opportunities along an EV user's travel-activity schedule. In absolute terms, all station types benefit from lower arrival energy levels, while higher arrival energy reduces station turnover. In relative terms, urban, refueling, and DC charging stations exhibit greater sensitivity to changes in arrival energy. For instance, a 1% decrease in arrival energy increases the average turnover of refueling stations by 1.5% and of parking stations by 1.4%. The higher sensitivity reflects the segment-specific user preferences discussed in Section 5.5. Stations where users exhibit strong preferences for departing with high energy levels, such as refueling or DC locations, respond more strongly to changes in arrival energy. Likewise, stations offering high utility at the current location, such as urban locations, appear to be more sensitive to changes in arrival energy content. In both cases, charging demand is either essential or a by-product of the user's activity at the current location, making station turnover particularly reactive to upstream energy availability.

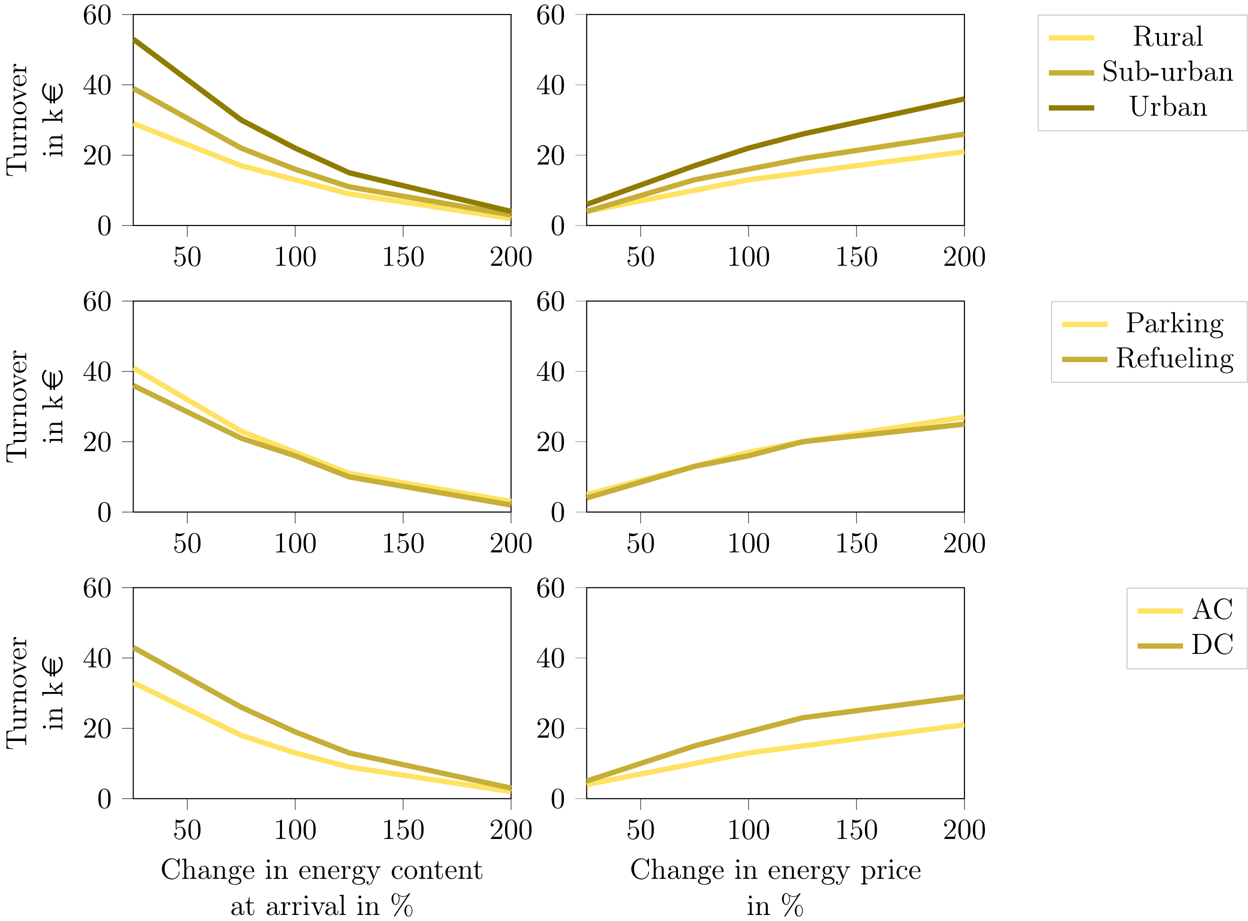

Figure 8: The mean of the total turnover over all charging stations in a single segment, depending on the decision margins relative to the arrival SoC and the energy price.

Energy price variations may have two effects on the total turnover of a charging station, a direct price effect on the total amount paid by an EV user and, indirectly, a quantity effect capturing the price elasticity of EV users' demand. Across all station segments, higher energy prices lead to increased absolute turnover, indicating that in the considered price range, the price effect outweighs the quantity effect. In relative terms, sub-urban, refueling, and DC stations are most sensitive to changes in the energy price. For example, a 1% increase in the energy price is associated with a 1% increase in turnover at refueling stations. The greater sensitivity may reflect two aspects of user preferences: (i) cost sensitivity, shaped by the availability of alternative charging options downstream in the travel-activity schedule or income levels, and (ii) the high valuation of energy at departure, shaped by downstream energy requirements. At refueling and DC charging stations, the demand for energy appears to outweigh users' cost sensitivity. Sub-urban locations combine higher cost sensitivity than urban areas with comparatively high energy valuation, resulting in greater responsiveness of turnover to price changes.

6. Discussion

The empirical case study has demonstrated that the utility from EV charging at public charging stations exhibits non-linearities regarding the product attributes energy content in the battery at departure and duration of the charging session. The results highlight the existence of an interaction term between both product attributes. When interpreting the findings and deriving implications, it is important to acknowledge certain limitations of the approach.

6.1. Interpretation

The case study observes a decreasing marginal utility regarding energy content in the battery at departure, in contrast to the assumption of constant marginal utility commonly adopted in the literature like in Liu et al. (2022) or Daina et al. (2017b). Only simulations, such as Fridgen et al. (2021) or Galus et al. (2012), consider the possibility of decreasing marginal utility. The observed decreasing marginal utility suggests that as users reach higher SoCs during a session, their perceived benefit diminishes. The observation indicates that marginal utility decreases once a sufficient SoC for the subsequent travel-activity schedule is reached. By demonstrating that the utility of energy content in the battery at departure varies non-linearly, this work highlights the potential for misinterpretation of users' preferences in models that assume constant marginal utility. Analogously, this paper reveals increasing marginal disutility regarding the duration of a session. Typically, models such as Daina et al. (2017b) or Nourinejad et al. (2016) assume constant marginal disutility from the duration of charging sessions. The increasing marginal disutility suggests, that with continuing time, the perceived harm of EV users staying at the charging station increases. The decreasing marginal disutility suggests that EV users may have a preferred departure time to be able to follow their travel-activity schedule. The urgency to leave the charging station may increase while approaching the ideal departure time.

According to the results of the case study, a significant interaction term between the energy content in the battery at departure and the duration of the charging session exists. To the best of the author's knowledge, commonly assumed utility functions for EV charging do not assume a dependence between the two attributes. The positive interaction between energy content in the battery and time spent at the charging station indicates that the marginal benefit from an additional unit of energy in the battery increases with the duration of the stay. The dependence of the marginal benefit from energy charged on the time spent indicates that the urgency to have a sufficient charge may increase when approaching the considered departure time.

On average, the value of time in a linear utility function would be 4.99 €/h and the value of energy 0.94 €/kWh. The value of time makes around 21% of the net wage in Germany (Statista, 2025). The value of energy leaves a consumer rent of 0.22 / €kWh in the case of DC charging and 0.36 €/kWh in the case of AC charging. The identified non-linearities imply significant changes in both the value of time and the value of energy around the average, depending on the SoC and the duration.

Charging stations in urban areas or at refueling locations, such as those along federal highways, tend to generate higher turnover than charging stations in rural areas. The turnover sensitivity simulations based on the estimated utility function suggest three potential links between user preferences and station viability: (i) a high valuation for energy content at departure, reflecting downstream energy requirements; (ii) low price sensitivity, potentially associated with higher income levels and a lack of competitive charging alternatives along the subsequent travel-activity schedule; and (iii) a lower sensitivity to charging duration, reflecting a high valuation of activities at the current location, whereby charging becomes a by-product of the ongoing stay.

6.2. Implication

The better performance of the non-linear utility function in contrast to the linear utility functions suggests that the structure of EV charging demand may be more heterogeneous than commonly assumed. While partially demand may be highly flexible, there may also be a significant share of inelastic charging demand.

Current energy system analysis and policies often assume EV charging demand to be highly flexible, driven by either constant marginal utility of energy or uniform price responsiveness. The observed decreasing marginal utility of energy charged, the decreasing disutility from charging duration, and the dependence between both attributes suggests that the flexibility may be more constrained than modelled. EV users may be less likely to adapt their charging behavior significantly when the SoC is insufficient and the travel-activity schedule imposes strict timing constraints. Consequently, the controllable capacity EV fleets contribute to the power system may be overestimated.

The profitability evaluation of different charging segments indicates that the investment spent on slow-charging public charging stations in rural areas may not be as beneficial. The segment differences and the sensitivity to the arrival energy content in the battery indicate that the interaction between private and public infrastructure must be considered. Public infrastructure that offers no power, location, or cost advantage over private infrastructure may turn redundant, particularly in areas where EV users have the option to install a private charging point.

6.3. Limitation

The data has properties that limit the generalization of the insights generated in the case study. Implicit in the dataset is a selection bias caused by two aspects. First, the early adopters of EVs that constitute the charging sessions reported in the dataset may not be representative of the entire population. Second, the dataset contains only publicly available and publicly funded charging stations. Charging stations that are financed without public funding are not part of the dataset so that the analysis may underestimate the turnover of charging stations.

The dataset does not contain information about individual circumstances of each charging session such as the arrival SoC of the batteries, the EV's battery capacity, and the actual tariffs paid. The assumptions taken may influence the observed results because they cannot account for the actual variance in circumstances. The analysis would benefit from a repetition with a more complete dataset.

The use of polynomial utility specifications, in the absence of individual-level user data, may limit the empirical identification and interpretability of non-linear marginal utilities. Appendix C.4 elaborates on the correlations between higher-order and base attributes, with the observed relationships indicating scope for further refinement and research. In particular, the absence of data on individual characteristics and planned departure times likely reduces the variance in observed choices, thereby weakening the identification of non-linearities in the utility function. Enhancing the dataset by incorporating preferred departure times and expanding the choice set to include more competitive charging alternatives along users' travel-activity schedules could improve the model's ability to capture marginal utility effects. One promising approach would be to intersect the charging demand data with longitudinal mobility surveys in Germany, such as KIT (2025), and to reformulate the charging decision as a dynamic discrete choice problem. Beyond travel behavior, incorporating information on individual risk preferences and behavioral characteristics may further improve model specification (Franke and Krems, 2013).

7. Conclusion

This paper examines the functional form of utility from charging an EV at a public charging station. It develops a novel discrete choice model that allows to estimate utility function coefficients given an operator's observed information at a charging point. Applied in a case study on a curated dataset of charging sessions at public charging stations in Germany, the approach reveals the suitability of different utility functions in describing charging choices, the underlying preferences of EV users, and the profitability of public charging stations.

The key contribution to the existing literature is threefold. First, the paper presents a discrete choice model formulation that allows to examine charging session data observed from the operator's perspective without information about individual characteristics. Second, the paper provides a comparison of different functional forms of utility from EV charging, derived from a description of EV users' preferences. Third, a case study obtains empirical support for the choice of utility function from a consistent dataset of revealed preferences, while contributing to the economic evaluation of charging station operation.

In the case study, it appears that the non-linear utility functions model the observed charging choices the most accurately. The findings suggest that marginal utility from energy charged is decreasing and marginal disutility from duration is increasing. Additionally, the results indicate that marginal utility from energy charged increases in duration. The insights suggest the flexibility of EV-charging is more constrained than commonly assumed. Distinguishing an elastic and inelastic part of energy demand from EV could illuminate the assessment of flexibility from EV-charging. Charging stations benefit from locations with inelastic residual charging demand, such as in urban areas or at traffic hubs.

The current research considers revealed preference data from public charging stations. Future research could analyze the preferences of EV users when charging at private locations, i.e., at home or work. Differences in the elasticity of demand at these locations could inform policymakers about the weighting between private and public charging infrastructure. The insights generated by the paper suggest that charging demand may be more heterogeneous than commonly assumed. Future work could explore the implications of refined assumptions about charging behavior for energy system analysis and charging station pricing strategies.

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Appendix A. Notation

Table A.6: Notation of the sets and parameters used.

Name	Definition
Sets	
$s \in S$	Charging event
S^{in}	In-sample charging sessions (training)
S^{out}	Out-of-sample charging sessions (test)
$j \in J$	Charging product
$m \in M$	Charging station
Parameter	
$\underline{E}^{arr}$	Minimum energy content in the battery at arrival
P^{AC}	Slow charging tariff
P^{DC}	Fast charging tariff
P^{Block}	Blocking fee
$\underline{t}^{Block}$	Start time blocking fee
$\overline{t}^{Block}$	End time blocking fee
δt	Time resolution

Table A.7: Notation of the variables used.

Name	Definition
Observable variables	
$t_s^{o,arr}$	Observed arrival time of charging event s
$t_s^{o,dep}$	Observed departure time of charging event s
ΔE_s^o	Observed energy charged during charging event s
Δt_s^o	Observed parking duration during charging event s
q_s^o	Observed charging rate during charging event s
Q_s^o	Available charging rates at the station of charging event s
$\overline{q}_s^o$	Maximum available charging rate at the station of charging event s
$\underline{q}_s^o$	Minimum available charging rate at the station of charging event s
j_s^o	Observed product choice in charging event s
Derived variables	
$\overline{E}_s$	Battery capacity of the EV in charging event s
$\overline{E}_s^{arr}$	Energy content in the battery at arrival in charging event s
T_s	Time horizon of charging event s
R_m^{Total}	Total turnover generated at charging station m
Product attributes	
$E_{s,j}^{dep}$	Battery's energy content at departure in charging event s of charging product j
$\Delta t_{s,j}$	Parking duration during charging event s of charging product j
$C_{s,j}$	Total cost in charging event s of charging product j
$C_{s,j}^{\Delta t}$	Duration component of total cost in charging event s of charging product j
$C_{s,j}^{E}$	Energy component total cost in charging event s of charging product j

Table A.8: Notation of functions used.

Name	Definition
Utility function coefficients	
ϵ_c	Unobservable factors affecting utility from charging product c
β	Nominal utility function coefficient
γ	Product cost coefficient
θ	Parameter of coefficient distribution
Functions	
$U_{c,s}^R$	Random utility from charging product c in charging event s
$U_{c,s}^N$	Nominal utility from charging product c in charging event s
$\mathcal{M}$	Discrete choice model (e.g., multinomial logit)
$\mathcal{P}(\overline{D}\|s)$	Probability density function of maximal charging duration $\overline{D}$ given charging event s
$\mathcal{P}(\underline{E}\|s)$	Probability density function of minimum energy charged $\underline{E}$ given charging event s

Appendix B. Data

Appendix B.1. Segments

The case study examines three segmentations, *Area*, *Activity*, and *Charger*. Table B.9 lists the segments of each segmentation and their assignment rule.

Table B.9: Segmentations applied in the case study and their assignment rules.

Segmentation	Segment	Assignment rule	Source
Area	Urban	71 Urban region - metropolis	BBSR (2023)
		72 Urban region - regional center and metropolis	
	Sub-Urban	73 Urban region - medium-sized city, urban area	
		75 Rural region - central town	
		76 Rural region - medium-sized city, urban area	
	Rural	74 Urban region - small-town, village area	
		77 Rural region - urban small-town, village area	
Activity	Parking	Public parking lot	NCfCI (2024)
		Customer parking lot	
		Parking garage	
		Park & Ride	
		Other	
	Refueling	Petrol station on a federal highway	
		Other filling station	
Charger	AC	$q < 50kW$	
	DC	$q \geq 50kW$	

Appendix B.2. Data imputation

The charging session data collected from charging station operators does not include information on specific choice circumstances. Instead, for each observed charging event s, the data includes details on product attributes such as the arrival and departure time ($t^{o,arr}$,$t^{o,dep}$), the connection duration Δt^o_s, the charged energy ΔE^o_s, the chosen charging power rate q^o_s, and the set of available power rates at the charging station Q^o_s. Based on the information provided, the dataset is enriched with additional assumptions regarding the battery capacity, the charging curve, the energy content at arrival, the time horizon, and the associated costs.

The construction of the choice set requires information on the EV's total battery capacity. A probability distribution $\mathcal{P}(\overline{E})$ is derived based on the battery capacity distribution of the current EV fleet, constructed by combining monthly data on the German vehicle stock from KBA (2024) with battery capacities of specific EVs models from ADAC (2024) as described in Appendix B.3. To account for the observed charged energy ΔE_s^o, which serves as the lower bound of the battery's capacity, the median of the resulting conditional distribution is taken as the assumed battery capacity $\overline{E}_s$ as formulized in equation (B.1).

$$\overline{E}_s = Med(\mathcal{P}(\overline{E}|\overline{E} \geq \Delta E_s^o)) \tag{B.1}$$

Charging at charging stations does not process with a constant power. While the exact charging power depends on various factors such as the EV or ambient temperature, most charging power curves decay in the SoC of the EV's battery because charging controls use a constant current-constant voltage (cc-cv) charging process instead of maintaining a constant power (Watson, 2022; Li et al., 2020). Appendix B.4 describes the charging curve assumption used in this paper. The dataset's energy charged parameter is measured at the connection point, including losses between charging point and battery. The products in the choice set account for losses of 15% (ADAC, 2022). A lower bound for the energy content in the battery at departure of a charging event is the energy content at arrival, E_s^{arr}, which itself is unobserved by the charging operator. Assuming that the observed charged energy was sufficient to fully charge the battery, $\overline{SoC}_s$ in equation (B.2) expresses the maximum possible SoC at arrival. Higher values would imply that the EV continues to charge at a high rate, although the battery's capacity is reached.

$$\overline{SoC}_s^{arr} = \frac{\overline{E}_s - E_s^o}{\overline{E}_s} \tag{B.2}$$

To evaluate whether the assumption of a fully charged battery is temporally feasible, the time required to charge from the maximum SoC to full capacity Δt_s^{full} is computed by equation (B.3) and compared to the actual observed connection duration Δt_s^o. Given the battery's capacity and the observed charging rate of the connection point q_s^o, an integral over the SoC-dependent charging curve $q_s(q_s^o, SoC)$ obtains the necessary charging duration. This paper assumes an exponentially decaying charging curve, as detailed in Appendix B.4.

$$\Delta t_s^{full} = \int_{\overline{SoC}_s^{arr}}^{1} \frac{\overline{E}_s}{q_s(q_s^o, SoC)} dSoC \tag{B.3}$$

The computed charging time distinguishes two cases, as shown in equation (B.4). If the observed charging time exceeds the charging time that would be needed to charge the battery fully, arriving with the maximum SoC, it is assumed that the battery is fully charged and the maximum SoC at arrival is indeed the arrival SoC. In any other case, the assumption does not hold, and the mean between a minimum assumed energy content at arrival $\underline{E}^{arr}$ and the maximum energy content at arrival $(\overline{E}_s - E_s^o)$ is taken as arrival energy content in the battery.

$$E_s^{arr} = \begin{cases} \overline{E}_s - E_s^o & \text{if } \Delta t_s^{full} \leq \Delta t_s^o \\ \frac{\underline{E}^{arr} + (\overline{E}_s - E_s^o)}{2} & \text{if } \Delta t_s^{full} > \Delta t_s^o \end{cases} \tag{B.4}$$

The time horizon T_s limiting the choice set of one observed charging event s is set to the time until which the lowest available charging rate $\underline{q}_s^o$ would take to fill the battery, adding one additional time step Δt to consider the option to stay connected beyond a full battery, shown in equation (B.5).

$$T_s = t_s^{arr} + \int_{SoC_s^{arr}}^{1} \frac{\overline{E}_s}{q_s(\underline{q}_s^o, SoC)} dSoC + \delta t \tag{B.5}$$

The charging product's costs $C_{s,j}$ consists of two components, one energy component $C_{s,j}^E$ and one duration component $C_{s,j}^{\Delta t}$.

$$C_{s,j} = C_{s,j}^E + C_{s,j}^{\Delta t} \tag{B.6}$$

Common EV charging tariffs distinguish charging rates by the type of connector, either alternating current (AC) or direct current (DC). AC chargers offer lower, DC chargers higher charging rates. Chargers with a charging rate below q^{fast} are considered to charge with the AC tariff P^{AC}, and chargers with a charging rate above q^{fast} are considered to charge with the DC tariff P^{DC}.

$$C_{s,j}^E = \begin{cases} P^{AC} \Delta E_{s,j} & \text{if } q_{s,j} \leq q^{fast} \\ P^{DC} \Delta E_{s,j} & \text{if } q_{s,j} > q^{fast} \end{cases} \tag{B.7}$$

The duration component depends on the parking time of the EV. Many tariffs include a blocking fee for occupying the charger, which starts after a certain parking time $\underline{t}^{Block}$ and must be paid by additional minute of connection $p^{Block} * t$. Appendix B.5 provides an overview of blocking fees. Some blocking fees have a limit, $\bar{t}^{Block}$, beyond which the blocking fee does not increase anymore.

$$C^D s, j = \begin{cases} 0 & \text{if } t \leq \underline{t}^{Block} \\ P^{Block} * t & \text{if } \underline{t}^{Block} \leq t \leq \bar{t}^{Block} \\ P^{Block} * \bar{t}^{Block} & \text{if } t \geq \bar{t}^{Block} \end{cases} \tag{B.8}$$

Both base tariff and blocking fee vary among operators and suppliers. The assumption taken here only captures the general structure of the tariffs, without accounting for contract-specific variation among EV users. The base tariff varies according to the charger type (EC, 2024). The blocking fee assumption bases on a review of several charging tariffs described in Appendix B.5.

Appendix B.3. Battery Sizes

The distribution of battery capacities follows the fleet of registered electric vehicles in Germany in the year 2023 taken from KBA (2024) and the battery capacity of the corresponding electric vehicle models provided by ADAC (2024). Figure B.9 illustrates the resulting battery size distribution. The mean capacity is 73 kWh.

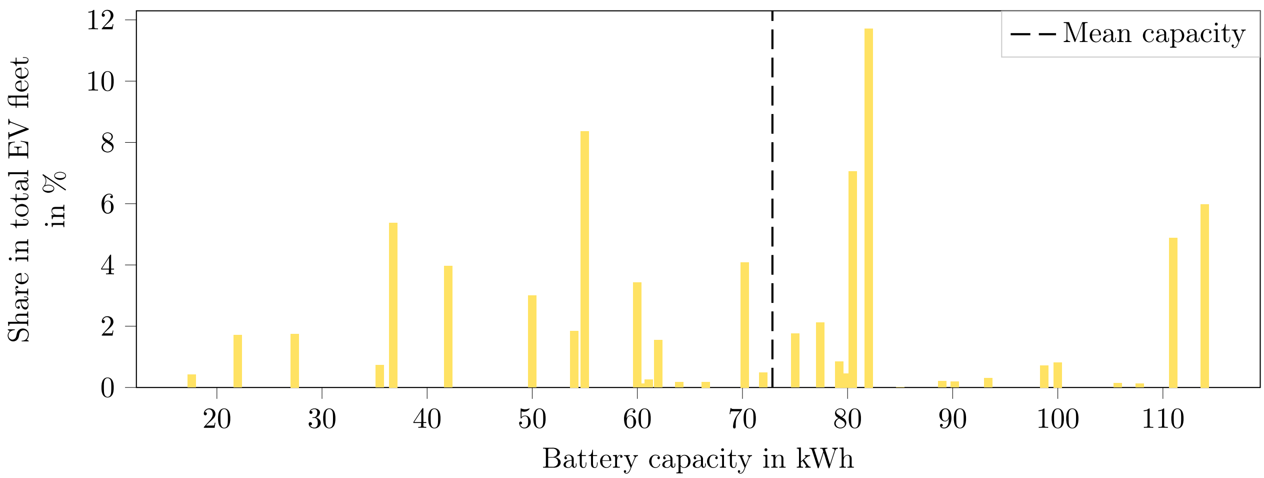

Figure B.9: The distribution of battery capacities in the German car fleet in the year 2023 based on KBA (2024) and ADAC (2024).

Appendix B.4. Charging curve

Electric vehicle charging does not maintain a constant charging rate throughout the process. Most charging power curves decay in the SoC of the electric vehicle's battery, (Watson, 2022) since the controls utilize a constant current-constant voltage (cc-cv) charging process (Li et al., 2020) instead of maintaining a constant power. A piecewise non-linear function comprising an initial constant power phase up to a switch point at the SoC SOC^{cc-cv}, followed by an exponentially decaying phase for higher SoCs, can model the resulting non-linear charging curve. Equation (B.9) describes the functional form of the assumed charging curve. The decay rate τ and the switching SoC SOC^{cc-cv} define the shape of the curve.

$$q(SoC) = \begin{cases} q_0 & \text{if } SoC \leq SOC^{cc-cv} \\ q_0 e^{-\tau(SoC - SOC^{cc-cv})} & \text{if } SoC > SOC^{cc-cv} \end{cases} \tag{B.9}$$

Figure B.10 depicts the assumed charging curve with $SOC^{cc-cv} = 50\%$ and $\tau = 2.8$. For comparison, the figure illustrates observed charging curves from Fastned (2025) and Schaden et al. (2021).

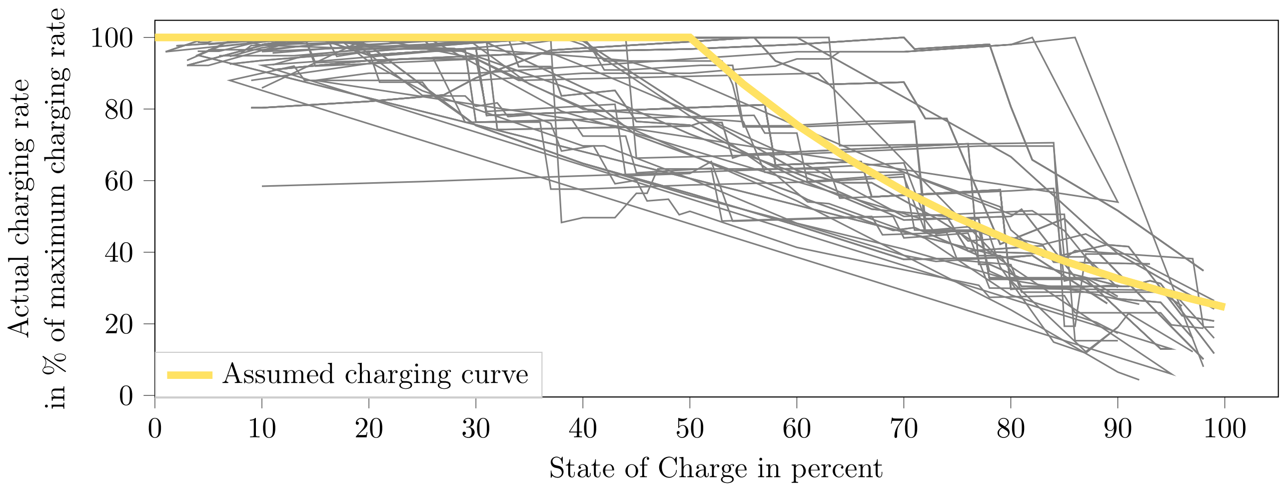

Figure B.10: Observed charging curves depending on the SoC based on Fastned (2025) and Schaden et al. (2021).

Appendix B.5. Blocking fee

Several German charging point operators charge a blocking fee for parking at a connection point (e.g. ENBW, 2024; Shell, 2024; SWD, 2024; ADAC, 2025; BMW, 2025; Elli, 2025; Entega, 2025; EWE go, 2025; IONITY, 2025; Lichtblick, 2025; MAINGAU, 2025; Mercedes, 2025; Sachsenenergie, 2025; SWM, 2025). Figure B.11 illustrates the total blocking fee charged under different blocking fee tariffs depending on the parking duration. As comparison, the figure shows the assumed blocking fee of 0.1 €/min given a free parking period of four hours and a maximum total blocking fee of 12 €.

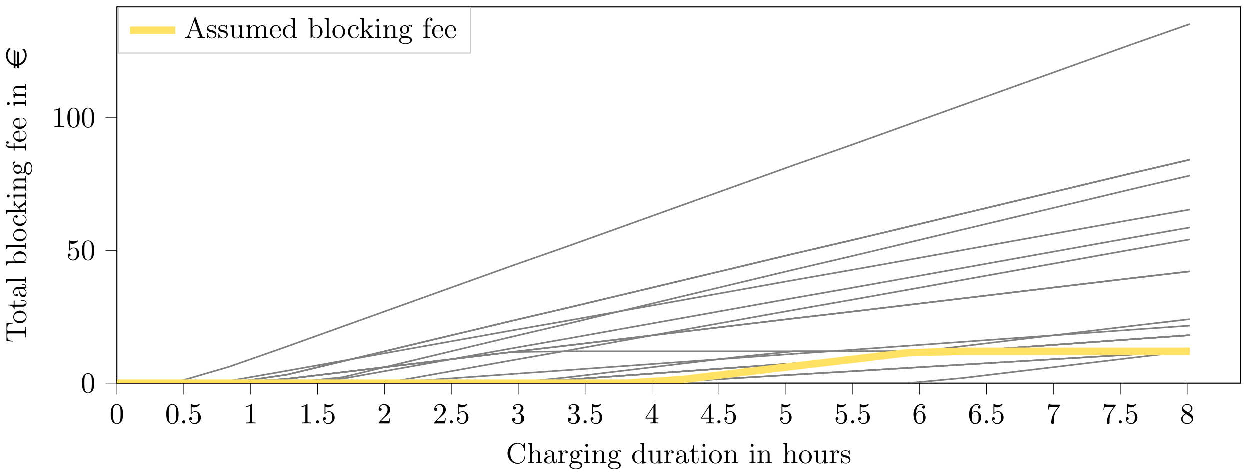

Figure B.11: An overview of blocking fees applied in German charging tariffs depending on the parking duration.

Appendix C. Robustness checks

Several design choices must be made throughout the case study, and these assumptions can influence the nature of the results. Assessing the sensitivity of model outcomes to alternative sampling strategies and design specifications helps demonstrate the robustness of the findings. As the examination relies on revealed preference data, inherent limitations may constrain the model's explanatory power. In particular, higher-order polynomial specifications are prone to higher correlations between the variables by construction. Examining the alternative specifications and variance structure offers insights into model assumptions and data limitations, highlighting opportunities for improving data sources and model specifications.

Appendix C.1. Sample size

The case study comprises 8,000 observations, randomly selected from a dataset of 1.03 million charging sessions 4.1. Varying the sample size may affect the results. Given the consistency of the estimators, such variations are not expected to distort the main conclusions of the case study (Wooldridge, 2016, p.169). Table C.10 shows the results from estimations based on 800 and 80,000 observations in columns (2) and (3). Across all sample sizes, the signs of the estimated coefficients remain stable, and the magnitude of coefficients evolves consistently in one direction, suggesting robustness in the underlying structural relationships. In the smallest sample, the coefficient for the quadratic duration term becomes statistically insignificant, indicating that a limited sample may lack the variation needed to identify more complex preference structures. The base specification in column (1), as used in the main case study, appears to include a sufficient number of observations to capture the utility structure reliably, thereby supporting the validity of the chosen data sample. Beyond the number of observations, the number of alternatives included in each choice set also influences the effective sample size. The number of alternatives in the case study is set by the resolution of the attributes energy, duration, and costs. Lower-resolution choice sets aggregate similar alternatives, potentially masking preference heterogeneity, whereas higher-resolution sets allow for more granular distinctions, but may introduce alternatives that are unrealistic or irrelevant from the perspective of EV users. In the case study, 162 charging alternatives are considered. Column (4) of Table C.10 reports the estimation results for a higher-resolution specification, comprising 1,003 alternatives. Column (5) further combines an increased number of observations (40,000) with a higher product resolution, resulting in 1,155 alternatives. the estimated coefficients retain their signs and significance levels, with one exception: the cost coefficient in column (4) becomes less significant. The number of observations may not be sufficient to identify preference differences given the larger set of alternatives. Consequently, increasing the number of observations in column (5) improves the significance. Regarding the magnitude of the coefficients, both expanding the choice set appear to induce directional convergence, further supporting the structural consistency of the model. The interaction term is the only coefficient where this pattern is less clear. A possible explanation is that lower-resolution choice sets may obscure subtler interaction effects between energy and duration. Nevertheless, the overall magnitude of the interaction coefficient remains within a comparable range, suggesting that the estimated utility structure is robust to changes in the level of attribute granularity and sample size.

Table C.10: Estimated coefficients of the Quadratic-in-Parameter utility function with interaction term for varying sample and choice set sizes.

	(1) Base	(2) $S^{in}\downarrow$	(3) $S^{in}\uparrow$	(4) $J\uparrow$	(5) $S^{in}\uparrow, J\uparrow$
	QiP Interaction	QiP Interaction	QiP Interaction	QiP Interaction	QiP Interaction
Costs	-0.056***	-0.106***	-0.024***	-0.024**	-0.021***
	(0.004)	(0.011)	(0.001)	(0.007)	(0.003)
Energy	0.498***	0.336***	0.544***	0.585***	0.604***
	(0.011)	(0.023)	(0.004)	0.021	0.010
Duration	-1.238***	-1.428***	-0.913***	-0.413***	-0.384***
	(0.086)	(0.278)	(0.029)	(0.174)	(0.084)
Energy^2	-0.004***	-0.002***	-0.005***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Duration^2	-0.052***	-0.006	-0.058***	-0.303***	-0.351***
	(0.006)	(0.008)	(0.004)	(0.033)	(0.025)
Interaction	0.020***	0.013***	0.016***	0.029***	0.030***
	(0.001)	(0.003)	(0.000)	(0.004)	(0.002)
Observations	8,000	800	80,000	8,000	40,000
Alternatives	162	148	204	1003	1155

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C.2. Sample composition

In discrete choice models, only differences in utility between products matter (Train, 2009, p. 24). The variance in observed product choices reveals the preference between products. Besides increasing the number of observations or number of alternatives, another option to increase the information carried by observed choices, is the pre-selection of observations. Particularly, given the extensive dataset used in the case study and the potential repetitive nature of observed charging sessions, sample selection may be a viable option to increase the variance in the discrete choice model improving the identification of preference structures in the discrete choice model.

Compared to the base case from the case study in column (1) of Table C.11, column (2) shows the estimation results when only observations are considered, in which the EV user chooses to depart with a full battery. Conversely, column (3) includes the results when only partial charges are considered. In the selected data sample of 8,000 observations, 2,598 correspond to full charges, leaving 5,402 as partial charges. The results for partial charges in column (3) largely align with the base case in terms of coefficient signs and significance. Only the quadratic term for duration becomes statistically insignificant, suggesting that full charges contribute important information regarding the increasing marginal disutility of charging duration—likely because they offer clearer insight into time preferences when departure energy levels are held constant. Accordingly, the coefficient for energy becomes larger in column (3), as preferences in the subset can be attributed more to differences in energy levels. In contrast, the estimation based on full charges in column (2) presents greater challenges for identifying the utility structure. Duration and interaction effects are not statistically significant, and the signs of the cost and quadratic energy terms deviate from expectations. Because energy levels are constant in the subset, only variation in time preferences can inform the model, limiting its explanatory power. Against this background, including both full and partial charges appears essential for adequately identifying the structure of charging preferences in EV usage.

A second option to increase the informational value of each observed choice is to restrict the sample to charging stations offering multiple power levels. In the base case, stations with only one available power level are excluded to ensure that each observed choice reflects preferences among a diverse set of charging alternatives (see Section 4.2). Table C.11 reports in column (4) the estimation results when all stations are included, regardless of the number of power levels, and in column (5) when only stations with at least three power levels are considered. In both cases, all coefficients remain statistically significant at the 1% level.

Including sessions from single-rate stations changes the signs of the duration and interaction terms. The shift likely reflects the reduced opportunity to observe preferences for faster charging, limiting the informational content about users' time sensitivity. In contrast, the estimates based on stations with three or more power levels are largely consistent with the base specification. Notably, the magnitude of the negative duration coefficient increases, potentially indicating stronger revealed time preference in charging decisions at the stations.

Table C.11: Estimated coefficients of the Quadratic-in-Parameter utility function with interaction term for observation pre-selection.

	(1) Base	(2) $E^{dep}_{s,j^o} = \overline{E_s}$	(3) $E^{dep}_{s,j^o} \neq \overline{E_s}$	(4) $Q^o_s > 0$	(5) $Q^o_s > 2$
	QiP Interaction	QiP Interaction	QiP Interaction	QiP Interaction	QiP Interaction
Costs	-0.056***	0.074***	-0.096***	-0.033***	-0.030***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.003)
Energy	0.498***	0.469***	0.750***	0.335***	0.364***
	(0.011)	(0.043)	(0.016)	(0.012)	(0.008)
Duration	-1.238***	-0.369	-0.681***	0.528***	-1.925***
	(0.086)	(–)	(0.095)	(0.078)	(0.087)
Energy^2	-0.004***	0.005***	-0.006***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Duration^2	-0.052***	-0.083***	0.002	-0.039***	-0.089***
	(0.006)	(0.010)	(0.003)	(0.004)	(0.005)
Interaction	0.020***	0.012	0.006***	-0.003***	0.030***
	(0.001)	(–)	(0.002)	(0.001)	(0.001)
Observations	8,000	2,598	5,402	8,000	8,000

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C.3. Alternative specific constants

In discrete choice modeling, alternative specific constants (ASCs) are commonly employed to capture unobserved variation in product choices that is not explained by observable attributes (Train, 2009). The constants absorb systematic differences in utility across alternatives that remain after accounting for observed characteristics. Beyond ASCs, individual-specific constants can reflect heterogeneity in preferences due to unobserved user characteristics, such as varying degrees of range anxiety or differences in time constraints and planning behavior (Franke and Krems, 2013). Another option would be to include station-specific constants, which can capture unobserved location-specific characteristics that systematically influence the choice of certain alternatives. These constants could reflect factors such as accessibility, nearby amenities, or perceived safety, which are not explicitly included in the model but may affect user preferences. Both individual-specific and station-specific constants are only relevant if their effect varies between products, so that actual choice differences are captured. Incorporating such elements improves the explanatory power of the model by accounting for individual-level variation in utility.

The product attributes in the considered charging choice model are discretized representations of continuous characteristics: charging duration, energy level at departure, and costs. Given that the discretized attributes already capture variation between alternatives explicitly, it is not immediately clear that ASCs would add explanatory power. Moreover, including ASCs for all more than 100 alternatives risks overparameterizing the model, leading to estimation challenges and potential overfitting. The dataset does not contain individual identifiers, which prevents linking observed charging sessions to specific users. As a result, it is not possible to include individual-specific constants in the model to account for unobserved user heterogeneity. Locational influences are partially captured by the segmentations in 5.4. It is notable, that the segmentation captures differences between observations and not necessarily between products.

While including ASC may overly burden the model, grouped constants can offer a feasible alternative to test the specification. In particular, user preferences may systematically differ by charging power level. Table C.12 compares the results of an $\text{ASC}^{\text{Power}}$ specification, that includes grouped ASCs by charging rate, to the base case from the case study. Two coefficients change in sign and significance: the cost coefficient turns positive, and the squared duration term becomes statistically insignificant. The sign reversal of the cost coefficient can be explained by the fact that charging costs are largely determined by the power level, with higher power chargers typically incurring higher per-kWh prices. The inclusion of ASCs by power level introduces finer granularity to the model, distinguishing between nine charging rates instead of the original two power-level groups. The additional differentiation absorbs the variation previously explained by the cost coefficient, indicating that the original specification already adequately captures power-related cost differences. Similarly, the insignificance of the squared duration term suggests that time preferences, previously captured through the curvature of the duration function, are now reflected in the choice between charging rates, which are directly encoded in the ASCs. Overall, the $\text{ASC}^{\text{Power}}$ specification appears to explain variance already accounted for by cost and duration attributes in the base model. Because this paper aims to identify structural utility functions based on observable product attributes, retaining a model that explains choices through costs, energy, and duration attributes, rather than group-level constants, offers greater interpretability.

Table C.12: Estimated coefficients of the Quadratic-in-Parameter utility function with interaction term with and without alternative specific constants (ASC).

	(1) Base	(2) ASC^{power}
	QiP Interaction	QiP Interaction
Costs	-0.056***	0.018***
	(0.004)	(0.002)
Energy	0.498***	0.614***
	(0.011)	(0.012)
Duration	-1.238***	-0.872***
	(0.086)	(0.049)
$Energy^2$	-0.004***	-0.005***
	(0.000)	(0.000)
$Duration^2$	-0.052***	-0.001
	(0.006)	(0.001)
Interaction	0.020***	0.009***
	(0.001)	(0.001)
ASC^{power}	No	Yes
Observations	8,000	40,000

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C.4. Correlation of coefficients

The case study focuses on higher-order utility functions. By design, the variables in such specifications are often correlated, which may also lead to stronger correlations among the estimated coefficients. While multicollinearity between estimators is not considered a well-defined problem in itself (Wooldridge, 2016, p.95), examining the correlation structure among coefficients can still provide valuable insights into the nature of the underlying estimation and potential issues of identification or redundancy in the specification.

Table C.13 presents the correlation matrix of the estimated coefficients, computed using Biogeme (Bierlaire, 2024). While there is no correlation that is problematic by definition, the coefficients for *Energy* and *Energy*^{2}, as well as for *Duration* and *Interaction*, exhibit relatively high correlations. The high correlation suggests that a substantial portion of the variance in the higher-order terms,*Energy*^{2} and *Interaction*, is explained by the respective base variables. As already indicated by the relatively low point estimates in Table 5.2, the high correlations reflect that marginal utility effects related to energy at departure are more nuanced and potentially harder to identify than for duration. As noted by Wooldridge (2016, p.96), such correlations are only indicative, and do not in themselves compromise a model. The low standard errors in Table 5.2 and the strong out-of-sample fit of the utility function including the higher-order terms shown in Section 5.1 support the conclusion that the correlations are not impairing model validity. The parameters remain informative, even though their explanatory power may be lower compared to the base variables.

Table C.13: The correlation between parameters for the Quadratic-in-Parameter utility function with the interaction term with in column (5) of Table 3.

	Energy	Duration	Energy^2	Duration^2	Interaction
Costs	-0.413***	0.192***	0.167***	-0.373***	-0.075***
Energy		-0.664***	-0.959***	-0.199***	0.67***
Duration			0.683***	0.334**	-0.959***
Energy^2				0.353	-0.738***
Duration^2					-0.561***

Further research could explore the higher-order components of the utility function in greater depth by extending both the case study and the model to better capture nuanced preferences. First, incorporating additional information on individual travel-activity schedules could improve the identification of preferences regarding departure energy levels, as the time constraints and urgency would be more clearly defined. Second, travel-activity schedules would allow for an expanded definition of the choice set, including not only the charging options available at the current station but also competitive alternatives encountered along the individual's planned route. Such an extension could provide a more comprehensive picture of EV users' preferences and improve the model's explanatory power.