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1. Introduction

1.1. Motivation

In the course of decarbonizing energy supply, the electricity system constitutes a central channel for providing low-emission energy to final consumers. Advanced economies promote electrification across sectors: electrolyzers for hydrogen production in industry, electric vehicles for individual mobility in transport, and heat pumps for residential heating (IAE, 2024, p.109). At the same time, the expansion of information and communication technology (ICT) increases electricity demand through the operation of digital infrastructure, partly offsetting efficiency gains (IAE, 2024, p.187). Germany showcases the global trends in its projected demand trajectory (EWI and BET, 2025, p.33-45).

From a microeconomic perspective, electrification expands the option set of final consumers by inserting electricity as an alternative to fossil fuels in the provision of energy services, such as material energy use, individual mobility, and residential heating. In making investment and usage decisions, consumers must account for the distinctive characteristics of the electricity system, which differ substantially from those of fossil fuels, for instance, in terms of its network-dependency and need for continuous balancing of supply and demand (Biggar and Hesamzadeh, 2014, p. 73-76). Unlike relatively stable fossil fuel markets, the short-term volatility of electricity markets may pose novel challenges for individual decision-making. At the same time, aggregated electricity demand may increasingly reflecs heterogeneous preferences regarding time, comfort, and location, thereby reshaping demand formation at the system level.

A more profound understanding of the determinants of emerging electricity demand is therefore essential. Examining the characteristics of electricity demand technologies, the factors influencing individual decisions, and the underlying user preferences provides insights into the drivers of power demand in the system transition. Such insights are valuable for informing multiple stakeholders: for individuals, to support informed decision-making when adopting new technologies; and for policymakers, to incorporate behavioral responses into the design of effective transition policies. At the system level, individual choices aggregate to affect electricity prices, network requirements, and investment needs, thereby influencing the efficiency and distributional outcomes of the energy transition.

To this end, this dissertation develops and applies methods for modeling and interpreting individual decisions in the system transition. It combines theoretical models, numerical optimization, and empirical approaches to capture different dimensions of emerging power demand. It examines how electricity market risks affect the viability of new technologies, how individual preferences shape demand patterns, how investment decisions in electric technologies interact with behavioral biases, and how digitalization influences final energy consumption. The applications focus on the German energy transition in the context of the European energy system. Each chapter is structured as a standalone research paper, contributing complementary perspectives to the overarching research agenda, resulting in the following structure:

- Chapter 2: Simultaneity of green energy and hydrogen production: Analyzing the dispatch of a grid-connected electrolyzer. Joint work with David Schlund, both authors contributed equally. Published in *Energy Policy* (Schlund and Theile, 2022).
- Chapter 3: The Shape of U – On the Structure of Utility from Electric Vehicle Charging. *EWI Working Paper 25/07* (Theile, 2025).
- Chapter 4: Environmental Policy Instruments for Investments in Backstop Technologies Under Present Bias - An Application to the Building Sector. Joint work with Fabian Arnold and Amir Ashour Novirdoust, all authors contributed equally. Published in *Environmental and Resource Economics* (Arnold et al., 2025).
- Chapter 5: Digitalization and energy consumption in the EU: sector-specific impacts and mediating factors. Markos Farag and Philipp Theile contributed equally, and Thomas Kopp reviewed and edited the text.

The remainder of the introduction provides an outline of the individual Chapters (Section 1.2), and discusses the methodological approaches, limitations, and opportunities for future research (Section 1.3).

1.2. Outline

Simultaneity of green energy and hydrogen production: Analyzing the dispatch of a grid-connected electrolyzer

Hydrogen production via grid-connected electrolyzers can entail unintended side effects, such as higher CO_2 emissions in power systems that are not fully renewable. To mitigate the indirect emissions, the EU introduces a simultaneity obligation (*temporal matching*), requiring hydrogen production to coincide with renewable generation within certain time intervals. Chapter 2 develops a model framework combining a mixed-integer linear program with a Markov chain Monte Carlo simulation for stochastic electricity market prices to assess electrolyzer dispatch. A case study of the German electricity market illustrates the effect of a simultaneity obligation on operational outcomes.

The results indicate that simultaneity reduces the CO_2 emission intensity of hydrogen production while constraining profits. The length of the simultaneity interval shapes the electrolyzer's average contribution margin and its profit at risk, reflecting exposure to renewable generation variability. Regulatory design at the electricity-hydrogen interface must consider the trade-offs between economic viability, full load hours, and associated emissions of electricity-based hydrogen.

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

With the growing adoption of electric vehicles, understanding user charging behavior becomes 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. Chapter 3 introduces a 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 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.

Environmental Policy Instruments for Investments in Backstop Technologies Under Present Bias - An Application to the Building Sector

Policies such as carbon pricing and subsidies are key to reducing greenhouse gas emissions. When individuals exhibit present bias, Heutel (2015) shows that the optimal policy mix for externality-producing durable goods includes one component addressing the externality and another correcting for present bias. Chapter 4 generalizes Heutel's model by broadening the technology set to reflect the dependence of fuel prices and emission intensities on building sector technologies and to include a zero-emission backstop technology. A theoretical part examines how the generalization modifies Heutel's propositions, distinguishing cases in which the backstop technology is or is not optimal. A case study of a representative German building quantifies the implications of present bias for heating system investment and use, emissions, policy performance, and deadweight loss.

Chapter 4 demonstrates that as long as social costs of carbon and the corresponding CO_2 price are insufficient to render the backstop technology optimal, Heutel's proposition holds: optimal policy must combine two instruments. Contrary to Heutel's proposition, once the social cost of carbon and the CO_2 price are high enough, a single instrument can address both the externality and present bias. While the optimal level of the single instrument, i.e., a tax or subsidy, depends on the level of present bias, the chapter finds that there exists a tax-subsidy combination that is optimal regardless of the level of present bias.

Digitalization and energy consumption in the EU: sector-specific impacts and mediating factors

Chapter 5 examines the relationship between digitalization and final energy and electricity consumption in the EU-28 from 2007 to 2020, with a focus on the industrial, transport, and residential sectors. Utilizing the system generalized method of moments (GMM), the chapter explores how the expansion of information and communication technology (ICT) capital impacts sector-specific energy consumption patterns.

The findings reveal that increased digitalization correlates with reductions in overall energy and electricity consumption, with a 10% increase in ICT capital share linked to a decrease of 0.74% in energy consumption and 0.47% in electricity consumption. Sectoral analyses demonstrate that digitalization lowers energy consumption in the industry and residential sectors, attributed to economic restructuring and efficiency improvements. In the transport sector, the impact of digitalization on energy consumption and efficiency is not statistically significant, suggesting barriers to digitalization's effectiveness. The analysis underscores the importance of considering sector-specific dynamics in understanding the relationship between digitalization and energy use.

1.3. Methodological approaches

Each chapter of this thesis addresses a distinct aspect of the economics of emerging power demand in the system transition, employing numerical, empirical, or theoretical methods. Chapters 2 - 4 adopt a microeconomic perspective, analyzing individual consumption, dispatch, and investment decisions. The analyzes model the respective actors as price takers and abstract from endogenous interdependencies between individual choices and system equilibrium. In the numerical models, the actors are assumed to have perfect foresight, resulting in a potential underestimation of their costs. Chapter 4 relaxes the individual focus and adopts a macroeconomic perspective, examining broader structural trends in energy demand.

Chapter 2 introduces a profit maximization model of a single electrolyzer connected to the electricity grid. A mixed-integer linear program (MILP) is developed to simulate grid-connected electrolyzer dispatch, incorporating a constraint that enforces simultaneity between renewable generation and hydrogen production. The dispatch model is simulated using several wind generation time series generated with a Markov chain Monte Carlo approach. The wind generation series are translated into electricity price series through a parametric model for intraday and day-ahead electricity markets.

The EU Emission Trading System (EU ETS) is the primary instrument for reducing emissions in the EU, establishing a cap on emissions in certain sectors. Since power sector emissions are capped, electricity consumed by electrolyzers may be regarded as emission-free. It is controversial whether requirements for hydrogen production are necessary or constitute double regulation. Chapter 2 does not address the interaction between hydrogen generation and the EU ETS, which remains an avenue for future research.

Chapter 3 establishes a discrete choice model framework based on revealed preference data to estimate utility function coefficients. It examines the functional form of utility from electric vehicle charging by characterizing products in terms of charging duration and energy delivered. Alternative specifications are compared, including linear and quadratic formulations of attribute utility as well as models with interaction terms.

The discrete choice model relies on revealed preference data from observed charging sessions at a single station but abstracts from individual-level information on EV users, such as budget and time constraints, activity preferences, and schedules. Consequently, observed charging demand is treated as an indirect outcome of underlying activity demand, e.g.,for leisure or work, subject to spatial and temporal constraints. The abstraction constitutes a key limitation, reducing the economic interpretability of the results. Future research could address the issue by combining charging session data with individual-level datasets, thereby enriching both the theoretical framework and empirical examination.

Chapter 4 comprises a theoretical and numerical part. The theoretical part generalizes an investment model for externality-producing durable goods developed by Heutel (2015) to encompass a broader technology set and a zero emission backstop technology. The numerical part applies the extended model as a nonlinear optimization problem to a stylized case study of a representative building in Germany, computing key outcome variables.

Household welfare-optimal decisions are evaluated using the *long-run criterion*. The criterion relies on a paternalistic assumption that present-biased household choices may deviate from their welfare-maximizing outcomes. While the assumption underpins the examination, it is open to critical scrutiny. Moreover, the *long-run criterion* constitutes only one of several possible criteria in settings with time-inconsistent discounting. Assessing the robustness of the chapter's findings under alternative criteria is a potential direction for future research. Further extensions could explore household heterogeneity, varying heating system vintages, and intertemporal investment dynamics.

Chapter 5 applies a mediation analysis framework to the relationship between energy consumption and information and communication technology capital. The analysis distinguishes structural and efficiency effects and introduces both aggregate and sectorally disaggregated energy and electricity consumption functions. Using the framework, the chapter examines the relationship between energy consumption and information and communication capital in the European Union from 2007 to 2020.

The examination uses information and communication technology capital as a proxy for digital development. While the approach provides a consistent and reliable measure, it does not fully capture recent dynamics, particularly changes in technology use. Future research could explore more nuanced indicators of digitalization. Despite the use of system GMM as a sophisticated estimator, the results should be interpreted as controlled correlations rather than causal effects. Unobserved country- or sector-specific factors may still jointly influence ICT capital and energy consumption. Extending the dataset and incorporating additional covariables to test the presented indications could further strengthen the findings. Finally, aggregating energy carriers may overlook technology-specific or structural effects of digitalization. Future research could address the shortcoming by using exergy-based or disaggregated energy measures.

Comprehensive descriptions of the methodological approaches as well as further research avenues are provided within the respective chapters.

2. Simultaneity of green energy and hydrogen production: Analyzing the dispatch of a grid-connected electrolyzer

2.1. Introduction

In the course of decarbonization, renewable primary energy carriers substitute fossil primary energy carriers (Smil, 2017). This transformation can be achieved by electrification of natural gas and oil applications, e.g., through heat pumps or electric vehicles, or by substituting hydrocarbons with climate-neutral gases like hydrogen or synthetic natural gas (Rosen et al., 2020, Thiel et al., 2016, Thomaßen et al., 2021). Hydrogen embodies characteristics that complement well the properties of electricity, e.g., it has a higher economic efficiency than electricity in some final energy conversion processes, such as heavy road transport, in high-temperature industry applications (Dodds et al., 2015, Parra et al., 2019), and steel production. Furthermore, it is a meaningful option for both short-term and long-term energy storage to balance fluctuating supply from intermittent wind and solar energy (Anderson and Leach, 2004). CO_2 emission reduction can only be achieved if no additional greenhouse gases are emitted for the production of hydrogen. A promising technology is, therefore, to produce renewable hydrogen from renewable energy (RE) sources and water electrolysis (Rosen et al., 2020). The latter is referred to as power-to-gas (PtG) technology, which uses electricity to split water into hydrogen and oxygen. Besides its positive effects on the energy system transformation, the uptake of hydrogen as a future energy carrier, new markets for hydrogen technologies and hydrogen trade can stimulate economic growth (Schlund et al., 2022), acknowledged by various governmental hydrogen strategies (Lambert and Schulte, 2021). However, so far, renewable hydrogen is economically not efficient in any final energy sector (Abdin et al., 2020, Buttler and Spliethoff, 2018). Moreover, most energy systems still have substantial fossil generation in their electricity supply mix; hence, producing hydrogen from fossil-fired power stations can increase CO_2 emissions from the power sector (Hurtubia and Sauma, 2021, Schlund and Schönfisch, 2021).

Policymakers are facing the challenge of building capacity for hydrogen generation to stimulate technology development while maintaining emission reduction measures in the power sector. Defining and certifying green hydrogen is one option to separate both goals, so that exclusively emission-free hydrogen production is favored by the regulatory framework (Velazquez Abad and Dodds, 2020). The design and effectiveness of such a separation are politically and scientifically discussed. A repeated part of these discussions is establishing a temporal link between electricity-based hydrogen generation and electricity generation from RE sources. For instance, in the EU (European Commission, 2018) or German (Renewable Energy Act, 2021) legislation this temporal link is considered. This temporal link can be expressed by the *simultaneity* of the power generation from the RE source and the power consumption. While the original rationale behind such a simultaneity obligation is the prevention of unwanted side-effects in the electrolyzer dispatch from investment subsidies, it may distort the investment signals. These possible distortions on the investment incentive have not been taken into consideration so far. In this paper, we assess the structural form of these distortions that policymakers can consider when designing dispatch-oriented criteria for green energy subsidies. Therefore, we focus on a grid-connected electrolyzer, which purchases electricity at spot markets and is obliged to consume electricity from RE plants. We explicitly consider and vary the simultaneity to assess four aspects of the obligation on the electrolyzer dispatch: the general value generated by the electrolyzer, the risk from varying RE generation, the sensitivity on the price relation between hydrogen and electricity, and the translation of associated carbon emissions.

Against this background, we develop a model framework including a mixed-integer-linear program to determine the optimal dispatch of an electrolyzer, a parametrical representation of day-ahead and intraday markets, and a Monte Carlo simulation to generate random wind generation. We apply the framework to an electrolyzer located in Germany and vary the electricity prices for the year 2019. We draw random wind generation realizations for this case and evaluate the distribution of the contribution margin and full load hours (FLH). We vary the simultaneity interval and assess its structural impact on the viability and associated emissions of the electrolyzer.

The remainder of the paper is structured as follows: Section 2.2 reviews recent literature on the economics of power-to-gas technology. Section 2.3 presents the model framework and the numerical assumptions for the case study, and Section 2.4 shows the results. In Section 2.5, we discuss the implications of our findings. We conclude our paper and draw policy implications in Section 2.6.

2.2. Literature review

The economics of power-to-hydrogen conversion has recently been subject to broad research. A PtG plant converts electricity into hydrogen, benefiting from cross-commodity trading between these two secondary energy carriers (Baumann et al., 2013). The economic viability strongly depends on the conversion efficiency and the market prices on the input and output side (Glenk and Reichelstein, 2019). The variable costs of a PtG plant are predominantly determined by electricity prices, which are increasingly characterized by the volatility of RE generation. The electricity procurement strategy significantly affects the hydrogen production costs and the total emissions of hydrogen production (El-Emam and Özcan, 2019). It can take three distinct forms: (i) The PtG plant is co-located and physically connected with a RE generation plant (Ferrero et al., 2016). The production of hydrogen is profitable when hydrogen sales yield higher revenues than selling electricity on the market, assuming that the RE generator is connected to the grid (Glenk and Reichelstein, 2019). If the RE generator and the public grid are not connected, hydrogen sales also need to cover the total cost of electricity generation (Brändle et al., 2021). (ii) Further, the PtG plant can be both connected to the public grid and co-located with a RE generator, forming a vertically integrated portfolio that can be optimized against volatile electricity prices (Clúa et al., 2018, Glenk and Reichelstein, 2020, Hurtubia and Sauma, 2021, Jørgensen and Ropenus, 2008). Moreover, (iii) a grid-connected PtG plant can be optimized against electricity market prices to maximize hydrogen production at minimal costs (Matute et al., 2021, Nguyen and Crow, 2016), whereby a distinction of different electricity pricing schemes (e.g., flat, time-of-use, or real-time pricing) can be made (Nguyen et al., 2019). In the third case, the PtG plant is more independent from volatile RE sources and can thus increase its output; however, indirect CO_2 emissions can be induced unless the electricity is entirely produced from RE (Huber et al., 2021).

Each power purchase strategy yields economic and operational constraints for the PtG dispatch, either through the availability of power supply or through electricity cost. A grid-connected PtG plant receives its renewable characteristic from the power source, which varies both temporally and spatially, and relies on the primary energy source used (Weber et al., 2010). Currently, hydrogen can either be sold to industrial consumers at (nearly) fixed prices (Luck et al., 2017) or sold as a close substitute to natural gas (Haeseldonckx and D'haeseleer, 2007). In the future, an equilibrium price of hydrogen at competitive hydrogen markets will equal the average cost of hydrogen production (Green et al., 2011). Since hydrogen is currently mainly used as a feedstock in industrial processes, there are only vague estimates on a possible equilibrium price. Thus, literature either considers inelastic demand in use cases for the industry, mobility, or heating sector or derives hydrogen prices from conventional production or derived products like synthetic methane (Baumann et al., 2013, Breyer et al., 2015, Fragiacomo and Genovese, 2020, Glenk and Reichelstein, 2019, Matute et al., 2019).

While numerous studies have estimated hydrogen production costs from grid-connected electrolysers with an optimization of the RE plant's and electrolyser's utilization, few have taken into account the indirect emission effect of electricity supplied by the grid. Since policies are in place or being discussed, defining regulation on electricity withdrawals from the grid to produce hydrogen, we aim at filling the gap in literature through explicitly focusing on a simultaneity obligation and its impact on hydrogen production.

2.3. Methodology

To answer the research question we develop a novel model framework and tailor a case study to an application in Germany.

2.3.1. Model framework

The model framework aims at capturing a realistic representation of an electrolyzer's operation, the volatility of a RE integrated electricity system, and appropriate metrics to assess the cross-commodity potential and the associated CO_2 emissions. Figure 2.1 summarizes the key components of our methodological approach.

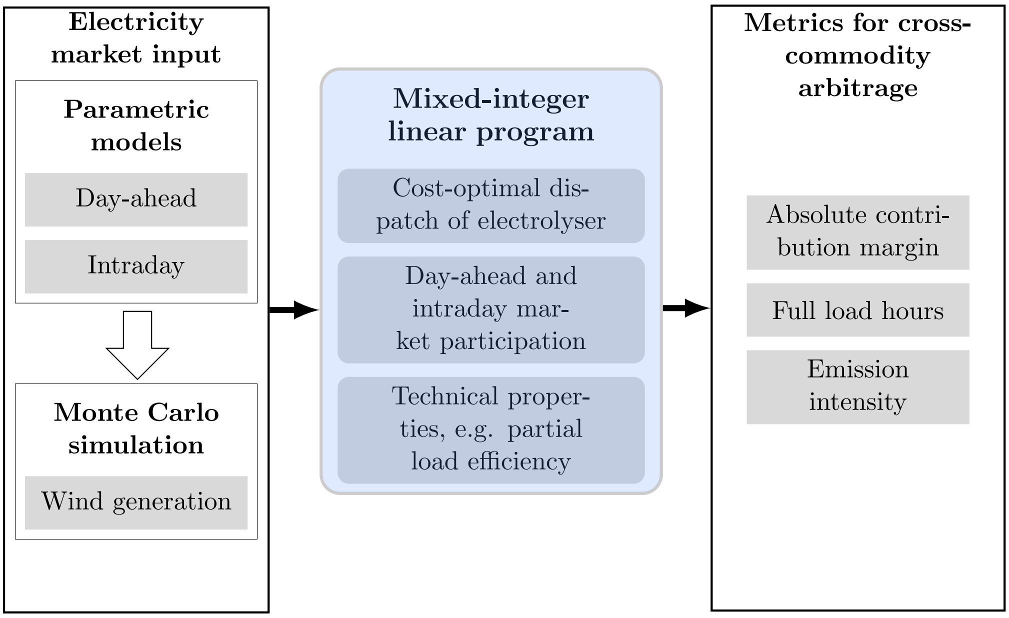

Figure 2.1.: Methodological approach consisting of a mixed-integer linear program, stochastic price time series generation, and metrics for cross-commodity arbitrage.

To estimate the optimal short-term viability of the electrolyzer, we develop a techno-economic mixed-integer linear program, which simulates the cost-optimal dispatch of an electrolyzer. The dispatch is optimized for exogenous wind generation and corresponding electricity prices. As electricity markets the day-ahead and the intraday market are considered. Other sources of revenue are not considered. Two parametric models for day-ahead and intraday electricity markets capture the relation between wind generation realizations and electricity prices. A Monte Carlo simulation of synthetic wind generation realizations includes the risk of uncertain wind generation. The models are applied in a case study for one year. Finally, we evaluate the case study with metrics for the viability and CO_2 intensity of the corresponding hydrogen production.

2.3.2. Mixed-integer linear program of electrolyzer operation

The economic viability of an electrolyzer depends on its variable cost, fixed operative and maintenance (O&M) costs, and revenues. In the short term, the cost-optimal dispatch of the electrolyzer requires that revenues are equal to or higher than the associated costs of the plant's operation. These decisions are modeled in the economic dispatch model, which simulates the operation of an electrolyzer under a temporal resolution of 15 minutes. Fixed O&M and investment costs are not considered in the short-term dispatch decision and, therefore, excluded from the dispatch model.

The economic dispatch model is formulated as a mixed-integer linear program (MILP). The objective function in equation (2.1) maximizes the profit over all simulated periods $t \in T$ from revenues R_t of hydrogen production and costs C_t of electricity supply.

$$\max \quad \mathit{Contribution\ margin} = \sum_{t}^{T} R_t - C_t \tag{2.1}$$

The revenue is calculated in equation (2.2) with an exogenous constant hydrogen price p^{H2} and the output of the plant, which depends on the load in period t and an input-output function f that converts electric input in MW into hydrogen output in kg considering a conversion efficiency. The output of the plant depends on its load L. The binary variable B determines whether the plant is switched on ($B = 1$) or off ($B = 0$). The constant δ ensures the correct time scale.

$$R_t = f(L_t, B_t) * \delta * p^{H2} \qquad \forall \ t \tag{2.2}$$

Equation (2.3) determines the variable cost of the electrolyzer. In each period t, the plant's load L purchased on the power market m is dispatched, whereby the set of markets M includes the day-ahead and intraday markets. The costs C are then calculated by multiplying the load with the corresponding electricity price p on the market and the fixed electricity surcharges α.

$$C_t = \sum_{m}^{M} L_{t,m} * (p_{t,m} + \alpha) * \delta^t \qquad \forall \ t \tag{2.3}$$

Its rated nominal capacity cap in MW_{el} limits the total load of the electrolyzer (equation (2.4)).

$$\sum_{m} L_{t,m} \leq cap \qquad \forall \ t \tag{2.4}$$

The minimal load constraint in equation (2.5) restricts the operating range of the electrolyzer. The minimal load is expressed as a share $\beta \in (0,1)$ of the nominal capacity *cap*.

$$\sum_{m} L_{t,m} \geq B_t * \beta * cap \qquad \forall \ t \tag{2.5}$$

The electrolyzer is assumed to be subject to a simultaneity obligation of RE and hydrogen production. The simultaneity is determined by a fixed time factor $\gamma \in T$, which defines the time interval in which RE generation and the electrolyzer's electricity consumption must be balanced. Hence, a time factor $\gamma = 1$ obliges the electrolyzer to consume the power production within the same period. If $\gamma > 1$, the electrolyzer can virtually shift the RE production from one period to another. The following equations operationalize the balancing of RE generation and hydrogen production. The sum of the total load L of one period t and all subsequent periods within the given simultaneity interval γ must be equal to or less than the RE production in the same period. The RE production is determined by the relative RE output re multiplied by the electrolyzer capacity *cap* and the RE scaling factor σ, which defines the capacity ratio of the RE plant and the electrolyzer. For the first periods ($t \leq \gamma$), the equation (2.6) is modified such that the latest period valid for balancing equals one. The simultaneity constraint implies that a virtual RE power storage is generated during the electrolyzer's operation, where RE power certificates are stored with a temporal validity of γ.

$$\sum_{m} L_{t,m} + \sum_{j=(t-\gamma+1)}^{t-1} \sum_{m} L_{j,m} \leq \sum_{j=t-\gamma+1}^{t} re_j * \sigma * cap \qquad \forall \ \gamma+1 \leq t \leq T \tag{2.6}$$

While the model formulation simplifies some technical characteristics and does not consider all the electrolyzer's business opportunities (e.g., frequency control), it comes with the advantage of low computation time. This allows solving the deterministic model for multiple realizations to follow a stochastic approach.

2.3.3. Synthetic electricity price time series

In a power system with a high share of RE, hydrogen production would rely on renewable primary energy carriers, such as wind and solar. The availability of these resources is intermittent, observable in electricity systems with high penetration of wind and solar generation. Since volatility will remain a crucial determinant of an RE system, we account for its impact on the electrolyzer's value. Beyond analyzing point observations based on a single weather realization, we capture the risk profile originating from the weather-dependency of renewable generation by performing two steps. First, we parameterize two linear models, one for the relation between RE generation forecasts and the day-ahead electricity prices and the other for the relation between the intraday prices, day-ahead prices, and forecast errors. Second, we generate synthetic renewable generation time-series with a Monte Carlo simulation as inputs for the independent variables in our linear models.

The first linear model captures the link between day-ahead electricity prices p_t^{DA} as the dependent variable and the residual load q_t^{res} as an independent variable. Equation (2.7) shows the corresponding model formulation (Burger et al., 2003). Note that we take the forecast residual load as an independent variable as it describes the available information at the day-ahead auction (Elberg and Hagspiel, 2015). We choose a third-degree polynomial so that it captures the non-linear relation between day-ahead prices and residual load (Ehrlich et al., 2015). The captured functional relation is not a pure estimate of the merit order but also includes the demand-side price elasticity implicitly (Elberg and Hagspiel, 2015). Additionally, ramp-up constraints, as well as scarcity situations, are addressed by the polynomial function. We fit one function per month so that the final model accounts for seasonal effects, e.g., wind generation, load, and resource prices.

$$p_t^{DA} = \epsilon_0 + \epsilon_1 q_t^{res} + \epsilon_2 (q_t^{res})^2 + \epsilon_3 (q_t^{res})^3 \tag{2.7}$$

The second polynomial model describes the relation between the intraday price p_t^{ID} as the dependent variable and the day-ahead price p_t^{DA} and the forecast error FE_t^2 as independent variables in equation (2.8). As we vary the wind generation, we model only the impact of forecast errors and day-ahead prices on the intraday price and let other influences remain unexplained (Hagemann, 2013). We use a second-degree polynomial model of the forecast error to account for the non-linear relation (Kulakov and Ziel, 2021, Narajewski and Ziel, 2020). Thus, our functional relation implicitly captures impact factors on the intraday price like scarcity situations and ramp-up constraints (Pape et al., 2016).

$$p_t^{ID} = \zeta_0 + \zeta_1 p_t^{DA} + \zeta_2 FE_t + \zeta_3 FE_t^2 \tag{2.8}$$

The parametric models capture the functional relation between wind generation, forecast errors, and electricity market prices. Following Papaefthymiou and Klockl (2008), we draw random wind generation and forecast time series. The creation of the Markov chain and the Monte Carlo simulation are explained in Appendix A.2. With these time series and the parametric models, we compute synthetic electricity price time series.

2.3.4. Evaluation metrics

The results are analyzed for the short-run profitability of an electrolyzer. First, the electrolyzer's annual contribution margin is evaluated, which is defined as the sum of hourly cost minus hourly revenues (see equation 2.1). Second, FLH for one year are determined: $FLH = \frac{Q}{Cap}$ (de Groot et al., 2017). Third, the CO_2 emission intensity of hydrogen is determined. Depending on the emission factor for electricity, the indirect carbon emissions of grid-connected electrolysers can be larger than zero, whereby either marginal or average emission factors can be used (Huber et al., 2021). An exact calculation of marginal emission factors and specific CO_2 emissions of hydrogen requires time-consuming electricity market simulations (Braeuer et al., 2020, Stöckl et al., 2021), which are not compatible with our stochastic Monte Carlo approach. We approximate the emission factor with two different measures to estimate a range of emission intensity of hydrogen.

We assume that matching renewable generation and hydrogen production in every 15-minute period as the lowest temporal unit of electricity balancing purposes in the EU, which we describe as a simultaneity of a quarter-hour, has an emission factor of 0 gCO_2/kWh_{el}[1], thus represents a perfect balancing of RE and hydrogen production[2]. Each (positive) deviation of the quarter-hourly power consumption from the RE generation leads to additional electricity demand, which must be balanced by the grid, where it increases the power production from the marginal power plant. The indirectly induced emissions are calculated by multiplying the total grid-power consumption with the emission factor for electricity in each period. We apply two emission factors for electricity: (i) The marginal emission factor (MEF) equals the specific emission factor of the marginal power plant, which sets the market price on the intraday market based on its marginal cost (Fleschutz et al., 2021). Hence, the marginal emission factor is determined by mapping the quarter-hourly intraday price with the marginal costs of different power plants. The yearly average grid emission factor (YAEF) is defined as the total emissions of the power sector divided by total electricity production and is constant throughout the year. Finally, the hydrogen emission intensity is calculated by dividing the total absolute CO_2 emissions (in kg) by the total absolute quantity of hydrogen produced (in kg).

Within the analysis, the obtained distributions of these three metrics are compared regarding their arithmetic mean value and their coefficient of variation (CoV). The CoV, or relative standard deviation, sets the standard deviation in relation to the mean of the distribution and measures the dispersion of a data set.

[1] We neglect embodied emissions in preliminary chains, e.g., for building, installing, and maintaining the wind generator and the electrolyzer. The emission balance should primarily capture the additional indirect emissions in the power sector from hydrogen production excluding additional embodied emissions.

[2] While even in the case of quarter-hourly simultaneity the actual emissions induced by the electrolyzer might be higher, the assumption enables comparability with higher simultaneity values.

The comparison focuses on general structures represented by relative changes to the base case rather than on absolute estimations.

2.3.5. Case study design

We simulate the model with historical German electricity market data and exemplary inputs for the electrolyzer. Electricity market data include day-ahead and intraday spot prices of the German electricity market zone from 2015 until 2019.[3] Generation, forecast, and realized electricity demand time series are withdrawn from the data publication platform of the German federal grid agency (German Federal Grid Agency, 2021). Electricity demand, generation, forecast, and intraday price data are available in quarter-hourly resolution, whereby day-ahead prices are given in hourly resolution. The simulation is run in quarter-hourly resolution for one year and 1000 samples of wind generation with accordingly derived electricity prices. The resulting parametric models for the electricity prices are shown in Appendix A.1.

The parameterization of the electrolyzer is based on literature data and summarized in Table 2.1. The ratio of the RE source and the electrolyzer capacity is fixed at a value of two, which is not endogenously optimized in the model and based on recent literature (Brändle et al., 2021, Glenk and Reichelstein, 2019). From the linearization of the input-output function, we receive a minimum efficiency at full load of 52 %, maximum efficiency at part-load of 61 %, and an average efficiency of 54 %. The efficiency values include peripheral equipment and refer to the higher heating value of hydrogen (Kopp et al., 2017). The assumed parameters only represent an exemplary electrolyzer. In practice, technical and economic characteristics are extensive and depend on multiple factors (see e.g., Götz et al. (2016), Saba et al. (2018), Thema et al. (2019)). Consequently, the simulation results depend on the parameterization of the electrolyzer. Based on current German regulation, we assume electricity price surcharges of 2.39 €/MWh.[4]

The initial exogenous hydrogen price is set to 3 €/kg in the base case and varied in a subsequent sensitivity (see Section 2.4.5). Currently, hydrogen is not traded on transparent and liquid markets. Instead, over-the-counter trades and bilateral contracts between producers and consumers organize volumes and prices. Here, we assume a selling price for green hydrogen as an indicator of the willingness to pay. The price is not varied over time since hydrogen can be stored, stabilizing the hydrogen prices (Green et al., 2011). The green characteristic is varied by changing the simultaneity obligation since it affects the renewable characteristic of the power supply.

[3]The year 2020 was excluded due to its low comparability with other years caused by the covid-19 pandemic.
[4]The surcharges consist of 1.54 €/MWh electricity tax and 0.85 €/MWh of other surcharges.

Table 2.1.: Electrolyzer parameter (own assumptions based on Kopp et al. (2017) and International Energy Agency (2019)).

Parameter	Value	Unit
Production capacity	1	MW_{el}
Ramping gradient	100	$\% \ \frac{cap}{15\ min}$
Minimum load	20	% of cap
CAPEX	800	$\frac{€}{kW_{el}}$
Lifetime	11	years
Fixed O&M costs	1.5	% of total invest
Interest rate	7	%

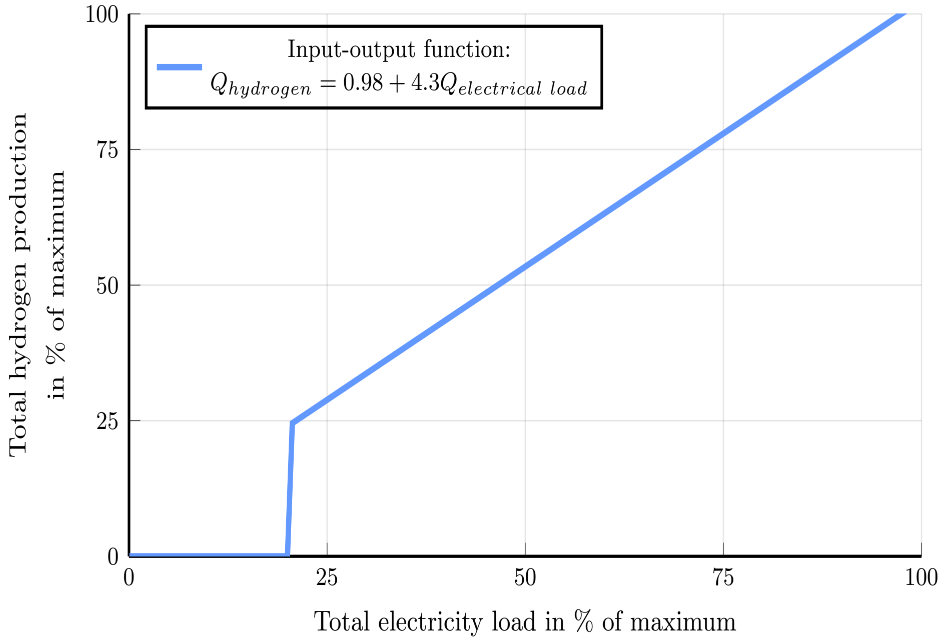

Figure 2.2.: Electrolyzer input-output-function (own assumption based on Kopp et al. (2017).

A reference list mapping MEF with electricity prices is derived from Fleschutz et al. (2021), which covers the German power system for the year of 2019. Hence, the MEF used from the study coincide with the data input for the regression analysis spatially and temporally for the most recent year. A day-ahead price of less than 35.5 EUR/MWh is below the lowest marginal cost of conventional power plants in the reference list. Hence, the marginal emission factor is assumed to be 0 gCO_2/kWh_{el} for prices below that threshold. As YAEF of Germany, we assume 408 gCO_2/kWh_{el} (Umweltbundesamt, 2021).

2.4. Results

We obtain results for the electrolyzer dispatch within the defined case study. First, we present the time series of randomly drawn wind generation realizations and corresponding electricity prices. For a base case, we show then the distribution of the absolute contribution margin and the FLH of a standardized electrolyzer. Fourth, we assess the impact of a simultaneity obligation on both the dispatch level and the annual dispatch risk. Fifth, the interdependence between a simultaneity obligation and the green hydrogen selling price is analyzed. Lastly, we highlight the effect on the CO_2 emission intensity of hydrogen.

2.4.1. Price time series

Based on the Markov chain, we generate 1000 samples of a yearly wind generation time series in quarter-hourly resolution. Combined with the parameterized day-ahead and intraday models, these wind generation samples obtain 1000 samples of quarter-hourly intraday prices and hourly day-ahead prices. Figure 2.3 illustrates the sampled range of these three time series. The two price time series diagrams show the upper and the lower limits of the sampled price duration curves, i.e. the sorted quarter-hourly electricity prices.[5] The lower diagram shows the range of the corresponding wind capacity factors.[6]

The middle illustration in Figure 2.3 shows the dispersion of the day-ahead price duration curves. Towards the lower and the upper end, the price dispersion increases. In the middle part, however, the dispersion is comparably low. The parametric models in A.1 represent the merit-order of the electricity market. The resulting price responses are stronger for particular high and low residual loads so that the differences between the samples in these periods lead to high

[5]The electricity prices are first sorted, and then the maximum and minimum of each sorted hour are shown in the respective diagram. They span the range of price duration curves within the total sample.

[6]The single samples are, first, sorted according to the order of the day-ahead price duration curves. Then the maximum and minimum of the wind capacity factor are shown in the diagram, also spanning the range of possible wind capacity factor realizations given the corresponding day-ahead price.

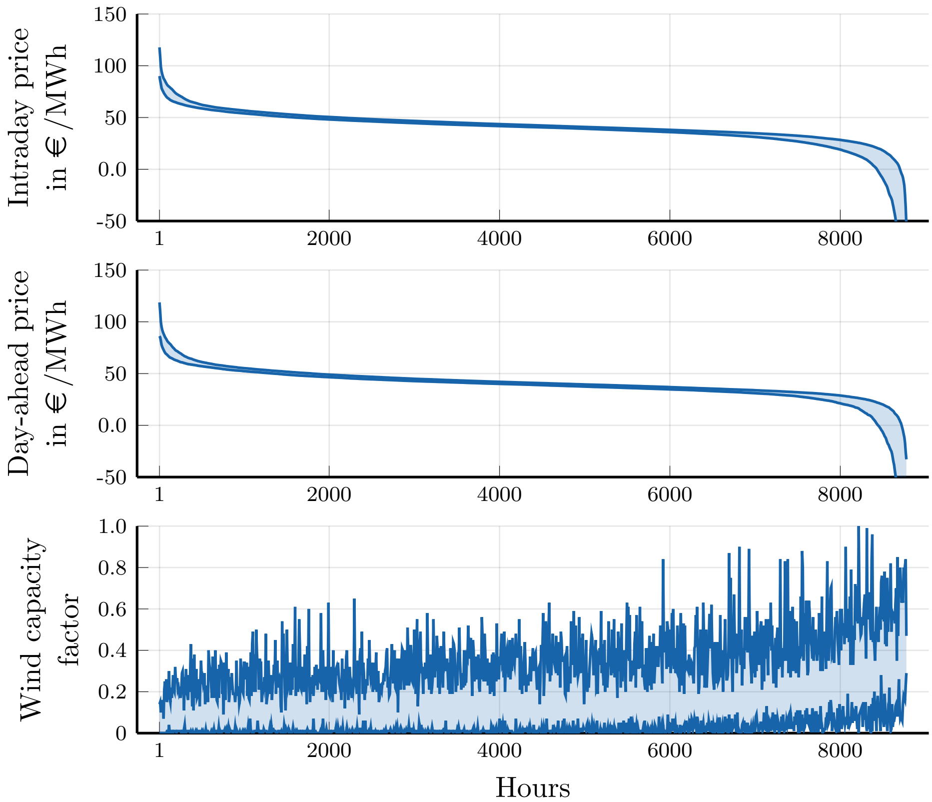

Figure 2.3.: The price duration curve of the intraday prices, the day-ahead prices, and the wind generation. The upper and lower limits of the sampled price duration curves are shown, and the wind generation's corresponding upper and lower limits.

dispersion in the price duration curves. Differences in the less extreme residuals translate into comparably low price differences. The illustrations show a negative correlation between the wind capacity factor and the electricity prices, indicating the merit-order effect of RE generation. Additionally, the figure shows that the dispersion of the wind capacity factor is higher in hours with low electricity prices. Electricity prices are mostly affected by wind generation when its feed-in is comparably high, resulting in a lower residual demand[7] (Sensfuß et al., 2008). This leads to lower prices when wind capacity factors are high and consequently to a higher dispersion of electricity prices depending on the variation of wind generation. The intraday price duration curve is quite similar to the day-ahead price duration curve as the source of variation is the wind generation forecast errors. These result in slight deviations from the day-ahead price.

Table 2.2 shows the descriptive statistics of the simulated time series and the resulting value factors for the wind generation profile. The mean yearly capacity

[7]Defined as total electricity demand less RE feed-in, which is the demand being supplied by conventional power plants.

Table 2.2.: Descriptive statistics of the samples wind generation and the regressed price time series.

Unit	Yearly capacity factor wind	Price day-ahead €/MWh	Price intraday €/MWh	Value factor day-ahead €/MWh	Value factor intraday €/MWh
Min	0.14	-149	-180	25	24
Max	0.18	106	106	37	37
Mean	0.16	40	41	33	33
StD	0.007	15	16	2	2

factor across all samples is 0.16, which equals approximately 1400 FLH. The minimum across all sampled years is 0.14 and the corresponding maximum is 0.18. The mean hourly electricity prices are 40 €/MWh for the day-ahead market and 41 €/MWh for the quarter-hourly intraday market, respectively. The mean of electricity price maxima deviates only in the decimals between day-ahead and intraday, while the mean of minima is 31 €/MWh lower on the intraday market. The value factors confirm the negative correlation between wind generation and electricity prices. The value factor of 33 €/MWh is lower than the mean average electricity price. The upper bound for the electricity market price, at which the electrolyzer is dispatched, depends on the green hydrogen selling price, which translates into an electricity break-even price through the plant-specific efficiency.

2.4.2. Dispatch of a grid-connected electrolyzer

A green hydrogen selling price of 3 €/kg and no simultaneity obligation define the base case. To understand the effects of higher simultaneity on the electrolyzer's dispatch, we first present the two main characteristics of this dispatch for the base case. First, we show the total profitability of the electrolyzer's dispatch indicated by the distribution of the absolute contribution margin (upper histogram in Figure 2.4). Consecutively, we show the electrolyzer's production rate indicated by the distribution of FLH (lower histogram in Figure 2.4).

The absolute contribution margin for a year ranges from 30 €/kW in the worst case to 61 €/kW in the best case. At the mean, the electrolyzer would generate a margin of 40 €/kW with a standard deviation of 5 €/kW. This results in a CoV of 0.12. The distribution is slightly right-skewed since it is more concentrated for low margins than for high margins. The underlying wind generation distribution initially causes the right skewness. Without simultaneity, it only affects the absolute contribution margin through electricity prices. The FLH show a symmetrical distribution with a mean of 3517 hours and a standard deviation of 115 hours. Since, in this case, the electrolyzer is not constrained by a wind generation profile, the FLH are determined by the hydrogen price, its cor-

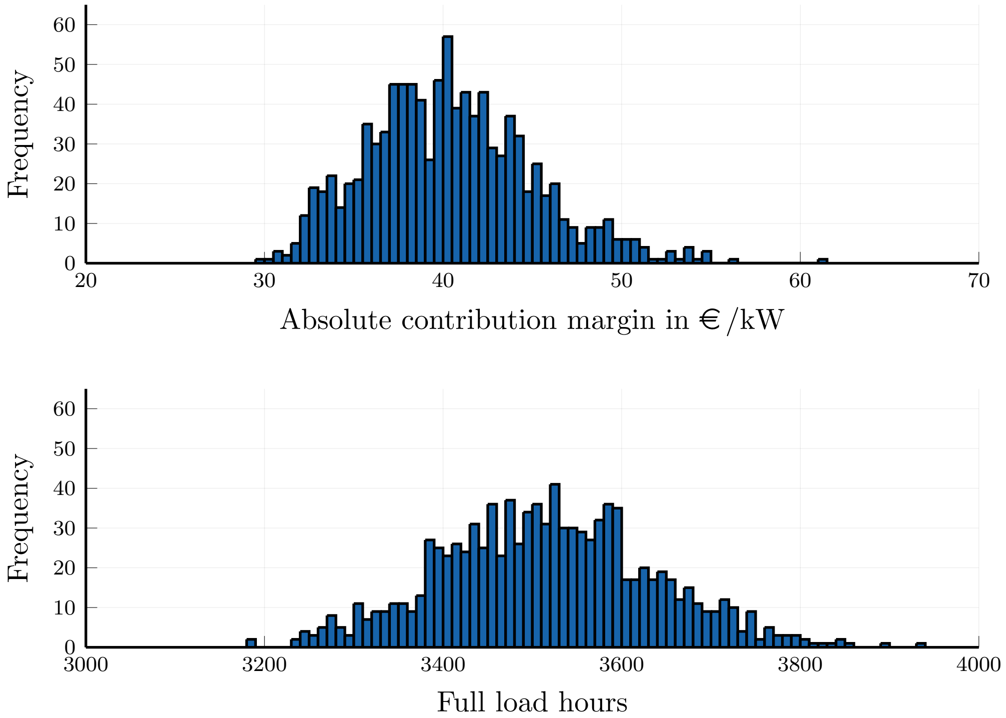

Figure 2.4.: The distribution of the absolute contribution margin (top) and the full load hours (bottom).

responding electricity break-even price, and the electricity price duration curve on the market.

The mean CO_2 emission intensities are 31.9 $kgCO_2/kg_{H2}$ when applying the MEF and 30.1 $kgCO_2/kg_{H2}$ using the YAEF. The break-even price defines the range of possible marginal power plants. From the mean FLH of 3517, we can derive the finding that the electrolyzer mostly operates in periods where electricity prices are either set by generation technologies with close-to-zero marginal costs, e.g., nuclear, RE or by baseload generation technologies, such as lignite power plants. Whereas the former has an emission factor for electricity of zero, the latter has the highest emission factor of all generation technologies. Consequently, the electrolyzer either withdraws power from the grid when the MEF is particularly high or low, which leads on average to a similar emission intensity of hydrogen compared to the YAEF.

2.4.3. Simultaneity effect on the annual dispatch level

Starting from the base case with a hydrogen selling price of 3 €/kg and no simultaneity, we first introduce a simultaneity of one year and increase it up to an interval of 15 minutes. The discrete intervals are *None*, 1 a, 12 hours, 8 hours, 1 hour, and 15 minutes. The hydrogen price remains constant. The results are normalized regarding the base case. The normalized means of the contribution margin and FLH are shown in Table 2.3.

Table 2.3.: Relative changes to the base case of mean, standard deviation, and coefficient of variation (CoV) of contribution margin and FLH in the simultaneity sensitivity.

	Simultaneity					
in % of base case	none	1a	12h	8h	1h	15min
Mean						
Contribution margin	100	98	78	75	71	67
Full load hours	100	78	57	54	51	47
Standard deviation						
Contribution margin	100	101	99	98	96	96
Full load hours	100	110	96	96	97	101
Coefficient of variation						
Contribution margin	100	104	126	130	135	143
Full load hours	100	141	170	178	189	216

The results show that the mean contribution margin decreases with an increasing simultaneity. Without any simultaneity, the absolute mean contribution margin results in a value of 40 €/kW. Compared to this, the contribution margin with simultaneity of 15 minutes is 33 % lower. The introduction of a yearly simultaneity would decrease the contribution margin by 2 %. The electrolyzer benefits from arbitrage since electricity can be bought during low-price periods and hydrogen can be sold at a fixed price. If no simultaneity obligation is in place, implicitly, all hydrogen produced by the electrolyzer is considered green, which can be interpreted as the virtual generation of the green electricity characteristic. The electrolyzer runs in all periods with an electricity price lower than the break-even price. The introduction of simultaneity ties the electrolyzer production to the wind generation profile. The electricity consumption is only considered green within a specific time interval and after its generation by the wind generator. Therefore, already yearly simultaneity prevents the virtual generation of green electricity. Implicitly, low simultaneity allows the electrolyzer to store the green characteristic of the electricity since it can generate the green characteristic in high-price periods and consume it in low price periods. The shorter the time interval, the lower the storage capability of the electrolyzer, and, hence, the lower the profit from this storage. Therefore, the case of a 15 minute simultaneity does not allow the electrolyzer to store the green characteristic and marks the lowest contribution margin with 67 % of the base case. The case of yearly simultaneity, on the other hand, implies the largest virtual storage, resulting in a contribution margin of 98 % of the base case. Thus, the potential value of virtual green electricity storage is significant and can make up to one-third of the electrolyzer's contribution margin.

The potential value of virtual storage also becomes apparent in the FLH. Without simultaneity, the mean FLH sum up to 3517 hours, corresponding to a capacity factor of 40 %. The introduction of yearly simultaneity reduces the FLH by 22 %. Compared to the base case *None*, where the break-even price alone determines the FLH, the total yearly production of the wind generator limits the FLH in case of yearly simultaneity. The 22 % difference marks the additional potential generation by a larger wind generation capacity for the electrolyzer. However, the 22 % FLH only account for 2 % of contribution margin. The electrolyzer mainly loses less profitable hydrogen generation at high electricity prices. Increasing the simultaneity further to 15 minutes results in an FLH reduction of 53 % compared to the base case. Compared to the case of yearly simultaneity, the reduction is 31 % points regarding the base case. Analogously to the contribution margin, the allowance to virtually store the green electricity characteristic can make up to 40 % of the electrolyzer's hydrogen production.

2.4.4. Simultaneity effect on the annual dispatch dispersion

The sensitivity of the contribution margin and FLH dispersion to a varying simultaneity is also shown in Table 2.3 in the form of the standard deviation and the coefficient of variation. The results are normalized regarding the base case.

The absolute CoV of the contribution margin in the base case results in 0.12 and increases with higher simultaneity. Introducing yearly simultaneity increases the CoV by 4 %. Reducing the interval to 15 minutes results in a CoV increase of 43 %. The allowance to store the green characteristic of the electricity generation increases the robustness of the electrolyzer towards varying yearly wind generation. In the case of yearly simultaneity, the dispersion between years with different wind generation realizations is defined by the lower end of the price duration curve (see Figure 2.3) since the electrolyzer can shift all of its power consumption into the lowest price periods. For simultaneity of 15 minutes, the dispersion between the yearly wind generation profiles mainly determines the dispersion of the contribution margin, as the electrolyzer cannot shift its consumption. The results indicate that the dispersion between the annual RE generation is higher than the dispersion between the yearly electricity prices, which finds support in the illustration of the time series in Figure 2.3. The variation within the wind capacity factor is higher than the variation within the electricity prices (see Table 2.2). Lower simultaneity decouples the contribution margin from the risk associated with the economic value of the wind generation profile. This risk can account for one-third of the total risk from yearly varying wind generation.

The CoV of FLH increases with a higher simultaneity. In the case of yearly simultaneity, the CoV is 41 % higher than in the base case (with an absolute value of 0.03). For simultaneity of 15 minutes, the CoV is 216 % of the base case's CoV. The simultaneity appears to have a more significant effect on hydrogen production risk than on the contribution margin risk. As already observed for the mean of the FLH, introducing a simultaneity obligation significantly in-

Table 2.4.: Absolute values of the mean contribution margin and the FLH at a hydrogen selling price of 3 €/kg.

	Unit	None	1a	15min
Mean contribution margin	€/kW	40.4	39.4	27.2
Mean FLH	h	3516	2740	1641

creases the CoV. Constraining the total yearly FLH to the wind generation limits the FLH of the electrolyzer, shifting the main dispatched hours to the high dispersion area at the low prices of the duration curve. Therefore, the dispersion increases significantly with the introduction of yearly simultaneity. Increasing the simultaneity further towards the 15 minutes interval increases the importance of the dispersion within the low electricity prices and the importance of the dispersion between the yearly wind generation profiles, since only wind generation within periods with prices below the break-even price leads to hydrogen production. Hence, the hydrogen production risk resulting from the wind energy profile makes up one-third of the total risk.

2.4.5. Interdependence of the simultaneity and the green hydrogen selling price

The hydrogen price is a decisive factor for the electrolyzer's viability, but it is generally unknown in the absence of a liquid hydrogen market. Therefore, a sensitivity is applied to the price. We simulate the electrolyzer dispatch model for a green hydrogen price of 2, 2.5, 3, 3.5, 4, and 4.5 €/kg. Three cases will be presented: starting from the base case (i) without a simultaneity obligation, the sensitivity is additionally applied on the simultaneity of (ii) one year and (iii) 15 minutes. In Table 2.4 the absolute values for the mean contribution margin and the FLH are summarized. Within each case, the relative deviation from a reference price of 3 €/kg is computed for the mean and the CoV of the contribution margin and the FLH. Figure 2.5 illustrates the results.

The diagram on the top left in Figure 2.5 illustrates the sensitivity of the contribution margin's mean to the hydrogen price for three simultaneity cases. Regardless of the simultaneity, the contribution margin increases with a rising hydrogen price. The exact gradient of this increase diverges between the different simultaneity obligations. In the absence of simultaneity, hydrogen production is profitable for all periods with an electricity price below the break-even price. Therefore, increasing the hydrogen price increases both the contribution margin for the already profitable periods and makes additional periods profitable. This twofold effect results in a convex contribution margin increase. Increasing the hydrogen price by 1.5 €/kg increases the contribution margin by 408 %. Introducing yearly simultaneity, the electrolyzer only profits from storing the green characteristic. As the FLH of the wind generation are limited, there is a saturation level of the contribution margin increase through higher production.

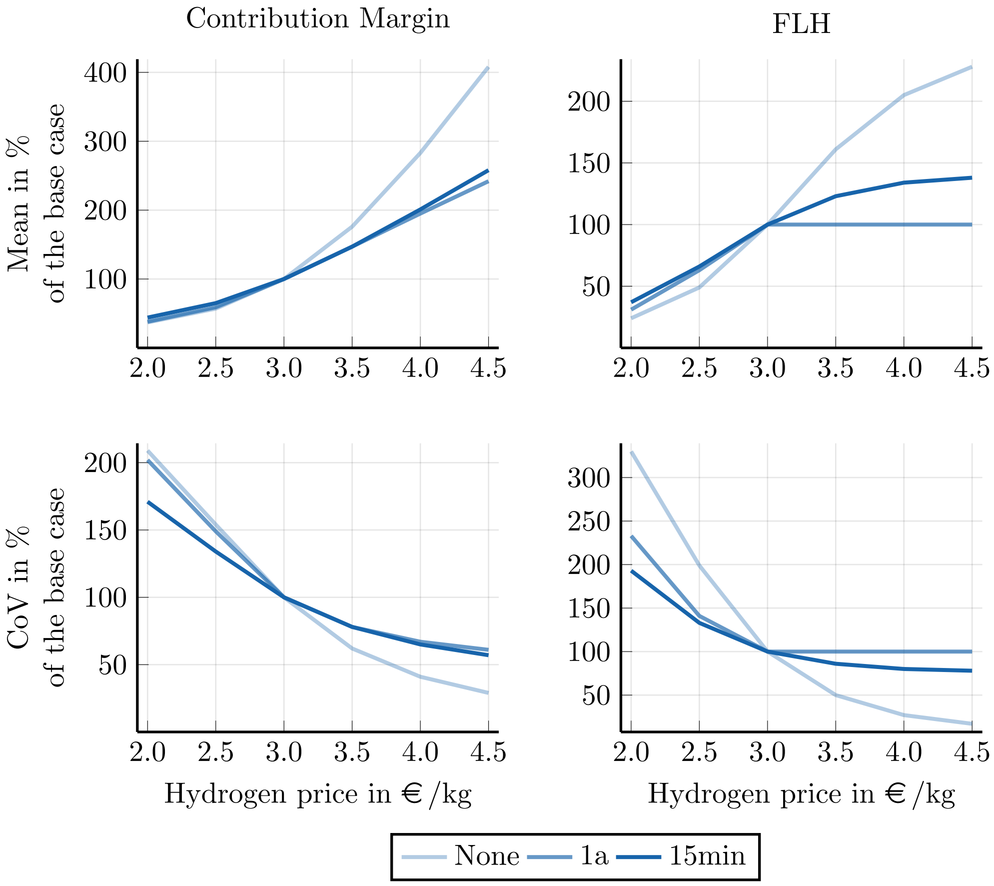

Figure 2.5.: Relative changes to the base case of 3 €/kg of the mean (upper) and the CoV (lower) of the contribution margin (left) and the FLH (right) in %.

Therefore, once the break-even price is sufficiently high to capture as many periods as FLH provided by the wind generator, the contribution margin increases linearly. At a hydrogen price of 4.5 €/kg, the contribution margin is 242 % of the contribution margin at 3 €/kg. With quarter-hourly simultaneity, the electrolyzer is also prevented from benefiting from green characteristic storage. This significantly reduces the mean contribution margin of the base case (see Table 2.4). However, the relative increase of the mean contribution margin is higher than with yearly simultaneity. With lower simultaneity and thus larger green characteristic storage, the electrolyzer reaches for lower hydrogen prices at the saturation level of the wind generation FLH. In the absence of the storage allowance, the electrolyzer reaches the saturation level not until higher hydrogen prices.

The relative changes of the FLH, and thus the total output of the electrolyzer, are shown in the top right diagram of Figure 2.5. The change in FLH is s-shaped, with a first convex increase, followed by a concave increase with a decreasing growth rate in FLH at a hydrogen price of more than 3.5 €/kg. The convex and concave course becomes most visible in the case of no simultaneity. For example, the FLH can be more than doubled (plus 105 %) when increasing the price from the base case (3 €/kg) to 4 €/kg, whereas it only increases by 67 % points when changing from 3.5 to 4.5 €/kg. This shape can be explained with the price duration curves in Figure 2.3. If the price is varied at a level such that the electricity break-even price lies in the flat part of the price duration curve, the number of operating periods is very sensitive to a change in the hydrogen price. If it is varied at the upper or lower end of the price duration curve with few prices at one level, the FLH are less sensitive to hydrogen price changes. Increasing the FLH is possible to a limited extent since electricity prices eventually reach the left tail of the price duration curve with soaring prices in a few hours of the year. Introducing yearly simultaneity adds a FLH saturation level based on the wind generation capacity factor. With the given assumptions, the maximum FLH are reached with a price of 3 €/kg. A further increase in the price enables the electrolyzer to be dispatched in more periods from an economic perspective (as shown in the first case without simultaneity). However, total wind energy production, i.e., virtual green electricity storage, is fully used. For simultaneity of 15 minutes, the FLH only increase with a higher hydrogen price when periods exist that have spare wind generation and electricity market prices above the electricity break-even price. Hence, the extent to which a higher hydrogen price increases the FLH in this situation strongly depends on the correlation between wind generation and electricity prices. Here, at a price of 3 €/kg, there are still periods with wind power generation but without hydrogen production, which allow increasing the electrolyzer's output at higher hydrogen prices.

The diagram on the bottom left in Figure 2.5 shows the contribution margin's CoV sensitivity to the hydrogen price. The relative CoV's resulting course shows a convex decrease for each line. In the case *None* without simultaneity, the CoV for a hydrogen price of 2.0 €/kg is 209 % of the CoV in the base case. For a hydrogen price of 4.5 €/kg, however, it decreases to 29 %. An increasing hydrogen price decreases the contribution margin's CoV in two ways. First, it defines the break-even price and, hence, the FLH and average short-term costs. A higher hydrogen selling price moves the break-even price along the flat part in the middle of the price duration curves. Here, the variation between the sampled years is low compared to the variation at the end of the price duration curve. With a higher hydrogen price, the share of the periods with prices, which vary little between the samples, in the total periods grows. This leads to a relative reduction of the CoV. Second, a higher hydrogen price increases the absolute contribution margin per kg of hydrogen produced. As the variation in the case without simultaneity only originates from the varying electricity prices, an increase of the revenue per kg decreases the relative impact of the production costs and thus the CoV of the contribution margin. In the case of yearly simultaneity, the electrolyzer's dispatch is constrained by the total FLH of the wind generator. Therefore, it already reaches for lower hydrogen prices a saturation level of CoV reduction than without simultaneity. For a hydrogen price of 4.5 €/kg, the relative CoV is 61 %. The electrolyzer only benefits from the first effect, i.e., the slight variation in the flat part of the price duration curve, until it reaches the wind generator's FLH. The second effect of increasing revenue compared to the cost variation remains. This also holds for the case of high simultaneity of 15 minutes. Although the FLH of the wind generator are exhausted for higher hydrogen prices (leading to a slightly higher CoV reduction rate), the CoV is mainly reduced due to the second effect for higher hydrogen prices. However, for lower hydrogen prices, the relative CoV increase is lower than for no and yearly simultaneity. While for no and yearly simultaneity, the price variation at the lower end of the price duration curve determines the CoV, the CoV in the case of high simultaneity is determined by the wind generation value factor. Due to the negative correlation between electricity prices and wind generation, the wind value factor has a lower dispersion than the electricity prices (see Table 2.2.

The FLH CoV's sensitivity to the hydrogen price is shown in the bottom right diagram of Figure 2.5. All curves show a convex decrease. The decrease rate is the highest for the case of no simultaneity, falling from 330 % of the base case's CoV for a hydrogen price of 2.0 €/kg to 17 % for a 4.5 €/kg. Again, two effects play a role in this decrease. First, the variation in the flat part of the price duration curve is lower than at its ends, resulting in a low CoV for break-even prices in this part. Second, for high hydrogen prices, the FLH of the electrolyzer are comparably high. Variation between the samples of a few hours only increases the CoV slightly. Therefore, the curve is convex in its reduction. Introducing yearly simultaneity adds a saturation level in the form of the wind generator's FLH. Therefore, once this saturation level is reached at 3 €/kg, the CoV does not change anymore. For lower hydrogen prices, the relative increase of the CoV is lower than in the case of no simultaneity. For 3 €/kg, the electrolyzer is already constrained by the FLH of the wind generator so that a further decrease in the hydrogen price has a relatively lower effect than in the case of no simultaneity. Given a quarter-hourly simultaneity, the CoV reaches the saturation level for higher hydrogen prices than under yearly simultaneity since the electrolyzer cannot shift its dispatch into periods with sufficiently low electricity prices. Analogously to the contribution margin, the CoV of the FLH increases with a lower rate for decreasing hydrogen prices.

2.4.6. Emission intensity

The additional value from storing the green characteristic of electricity comes with a potential fading of the actual greenness of the associated electricity consumption. The additionally induced electricity generation of conventional power plants to serve the electrolyzer's demand may increase indirect emissions. This issue does not only apply to the operation of electrolyzers but also to other power consumers (e.g., battery electric vehicles (Nansai et al., 2002)and demand-side response (Fleschutz et al., 2021)). The relative emission intensity of hydrogen to the base case is determined for each considered simultaneity. Furthermore, the mean emission intensities are determined for varying hydrogen prices along with the simultaneity of *None*, one year, and 15 minutes.

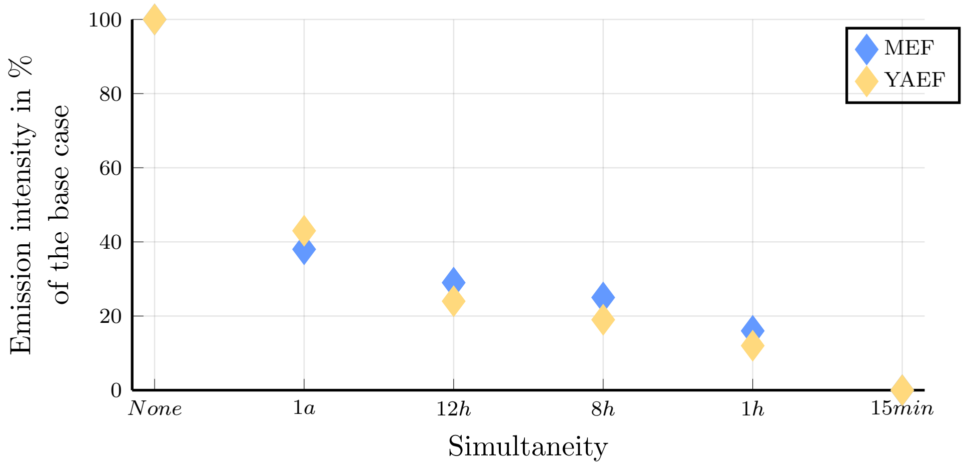

Figure 2.6.: The hydrogen emission intensity in % indicated by the MEF and the YAEF depending on the simultaneity.

In Figure 2.6, the mean CO_2 emission intensity of hydrogen for the simultaneity sensitivity is visualized. Starting from the case of no simultaneity, the relative average emission intensity is shown for each considered simultaneity. The case without simultaneity has the highest relative emission intensity since the grid fully balances the electricity consumption. Following the assumptions in Section 2.3, a quarter-hourly simultaneity corresponds to perfect balancing of RE and hydrogen generation and induces no additional indirect CO_2 emissions. Hence, the emission intensity of hydrogen is 100 % lower compared to the base case. The trend indicates a reduction in emission intensity with increasing simultaneity in between these cases. The largest drop occurs when a simultaneity obligation is imposed, i.e., moving from no simultaneity towards yearly simultaneity. Here, the emission intensity decreases by more than 50 % for both the YAEF and the MEF.

Moving downwards from yearly to lower simultaneity in discrete steps, the emission intensity further decreases, but the effect weakens. Note that the time intervals between the simultaneity cases differ, and the change in emission intensity must be regarded relative to the respective interval. The difference between 12 hourly and 8 hourly simultaneity is only 6 % points for the MEF and 5 % points for the YAEF, respectively. With simultaneity of 8 hours, the emission intensity of hydrogen reduces by more than two-thirds compared to the base case (*None*). A substantial decrease can be noticed when moving from hourly to quarter-hourly simultaneity, i.e., to perfect balancing, where the emission intensity decreases by more than 10 % points in both cases, although the step is the lowest on a time-scale. When comparing the results for yearly with quarter-hourly simultaneity, the relative emission intensity deviates by a value of 38 %

points. The effect of the simultaneity on the emission intensity appears to be very similar for both emission factors for electricity. This implies that higher simultaneity reduces the share of electricity balanced from the grid, but the average mean emission factor for electricity does not change significantly.

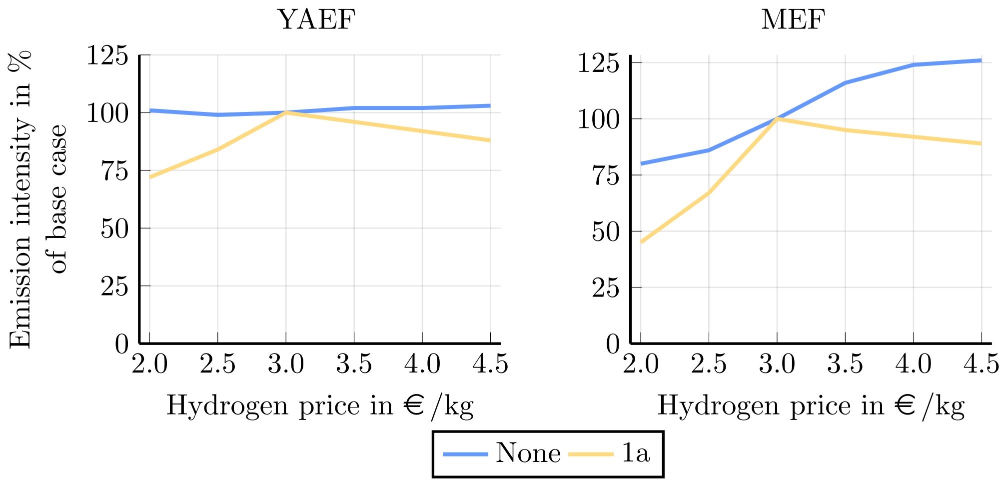

Figure 2.7.: The relative hydrogen emission intensity to the base case (3 € /kg) indicated by the YAEF (left) and the MEF (right) for the hydrogen price sensitivity.

Besides the simultaneity, the hydrogen price can affect the emission intensity of hydrogen since it changes the electricity break-even price and, therefore, the possible range of marginal power plants. The charts in Figure 2.7 show the relative emission intensity of hydrogen depending on the price for yearly and no simultaneity when applying the MEF (left chart) and the YAEF (right chart). The emission intensity for quarter-hourly simultaneity is not displayed, as it does not change with the price and always equals zero in absolute terms.

Applying the YAEF, the emission intensity does not change when no simultaneity obligation is in place since both the emission factor for electricity and the power balanced by the grid are constant overall prices. With yearly simultaneity, the emission intensity depends on the share of electricity that exceeds the generation from the RE sources and is balanced by the grid. The mean emission intensity of hydrogen decreases when the hydrogen price is reduced from the base case price of 3 € /kg. Low electricity prices usually occur when residual demand is low and when RE feed-in is high. With increasing residual demand, the electricity market price rises and the share of electricity, which is balanced by the grid, increases. Consequently, a comparably low selling price for green hydrogen limits the electrolyzer to produce only in periods with low electricity prices and accordingly high feed-in from the RE generator, which means that less power must be balanced by the grid, lowering the emission intensity of hydrogen. However, a comparably higher price with yearly simultaneity also decreases the emission intensity. Here, the emission intensity hits its maximum at 3 € /kg and slightly decreases afterward. While the mean FLH reach the maximum with a price of 3 €/kg and do not increase with higher prices (see Section 2.4.5), the considered part-load efficiency allows the electrolyzer to increase the total output by using the same amount of electricity. In a small range of electricity benchmark prices, it is economically efficient for the electrolyzer to operate in partial load to increase efficiency and accept a lower output. With a higher hydrogen price, this price range increases, and the operating periods with partial load shift towards higher electricity market prices. As a result, the total output of the electrolyzer increases while the consumed power remains constant, which leads to a slightly lower emission intensity of hydrogen with a higher hydrogen price.

Applying the MEF, the emission intensity of hydrogen increases with the hydrogen price when no simultaneity obligation is in place. The change is S-shaped, meaning more minor deviations from the base case with a price of 3 €/kg lead to more substantial emission effects than higher deviations. The MEF depends-besides the rate of power balanced by the grid-on the electricity market price. With higher prices, the electrolyzer can also be dispatched during mid and peak load periods, which can be seen by the increased FLH with a higher price (see Section 2.4.5). In these periods, coal- and gas-fired power plants are often marginal suppliers, which have lower emission factors in comparison to lignite power plants. Hence, the increase in indirect emissions is slowed down. With yearly simultaneity and applying the MEF, the trend of the mean emission intensity is similar to the YAEF, but the decrease at lower prices is stronger when applying the MEF. Since the MEF depends on both the share of power balanced on the grid and on the electricity market price, the effect of the marginal power plant affects the emission intensity in two ways: the MEF is lower at a comparably lower hydrogen price, and the power supply from the RE generator is higher since it often produces in periods with low electricity prices. On the other hand, the emission intensity decreases with a higher hydrogen price and yearly simultaneity. The effect is analogous to the YAEF reasoned by the increase in output with the same FLH, but the emission intensity is affected by the electricity price and the change in total output.

2.5. Discussion

This chapter presents the dispatch decision of an electrolyzer, highlighting the impact of a simultaneity obligation of hydrogen and electricity generation from RE sources in the presence of risk from varying wind generation. Since grid-connected electrolyzers could physically operate constantly and without restrictions from the supply side, the simultaneity obligation is a political measure to tie electricity consumption to its production from RE plants to prevent fossil-fired power plants from supplying PtG plants with electricity. Hence, the simultaneity can be interpreted as an allowance to store the green characteristic of the RE plant's electricity generation. In the case study, we show that this allowance improves the business case of an electrolyzer in three ways. First, the storage capability adds economic value to the dispatch of the electrolyzer. The electrolyzer benefits from time arbitrage, shifting the green characteristic from high-price to low-price periods. This arbitrage increases the electrolyzer's contribution margin. Second, the virtual storage also mitigates the RE generation risk, both price and quantity. Third, the contribution margin's sensitivity to green hydrogen price changes is higher. The electrolyzer benefits directly from higher hydrogen prices as it can shift it to periods in which the electricity price is sufficiently low. These three aspects also hold for the hydrogen production quantity.

One goal of a simultaneity obligation is the prevention of additional indirect CO_2 emissions from grid-connected electrolysers. During the hydrogen market ramp-up, the electricity supply mix has still significant shares of conventional power generation, translating, if not constrained, into a high emission intensity of hydrogen. Our results have shown that simultaneity, indeed, affects the electrolyzer's dispatch of its emissions. From a system perspective, a reduction of emissions can be achieved if additionally generated renewable electricity is used to produce renewable hydrogen. As a consequence, RE generators sourcing the electrolyzer should be installed to the existing capacities simultaneously to prevent additional emissions from the power sector. Otherwise, hydrogen production would displace RE production from existing generators and ultimately lead to additional generation from fossil-fired plants to serve residual electricity demand (see e.g., Pototschnig (2021)). The installation of RE capacities along with the electrolyzer investment needs to be ensured to meet additional electricity demand from hydrogen generation with zero-emission production. Another aspect to be considered at the system level is the fact that the European power sector is part of the EU ETS, where the total emission budget is theoretically limited. However, in practice the market stability reserve (MSR) softens this limit. Increased emissions from electricity generation for the purpose of hydrogen production can lead to lower cancellation of emission allowances in the short-term or even higher emission allowance auction volumes. To what extent the emission demand from hydrogen production would displace emission demand, or rather increase overall emissions, remains ambiguous. The dynamic design of the EU ETS prevents a definite determination of the emission effect from hydrogen production (Bocklet et al., 2019, Schmidt, 2020). Generally, regulation may tend to tailor different green characteristic definitions to each emission mitigation option. However, maintaining these various definitions in parallel may induce distortions not only between green and non-green technologies but also within green technologies. If a policy instrument for internalizing the costs of emissions is already in place, such as the EU ETS, additional restrictions on the dispatch of electrolyzers may not be necessary. Regardless of the indirect effect on emissions in the short-term, the simultaneity obligation may have a due date since it becomes obsolete with higher shares of RE in the electricity supply mix.

Given the dependence of the short-term dispatch decision on the RE generation risk and the simultaneity, it is of interest for an investor how these conditions affect the long-term profitability. The profits must cover the annuity and other fixed costs to make the electrolyzer investment viable. Taking the assumptions of the case study from Section 2.3.5 on investment cost, depreciation time, and interest rate, we can derive an annuity (including fixed cost) of 119 € /kW. Comparing the fixed and annuity costs to the mean contribution margin from the base case of 40 € /kW, the investment would prove unprofitable with a financing gap of approximately 80 € /kW. Given a standard deviation of 5 € /kW, even in the more advantageous cases, the electrolyzer cannot cover its long-term cost. The relative risk of the contribution margin—expressed as CoV in Section 2.4-increases with the simultaneity by up to 43 % when changing from *None* to quarter-hourly simultaneity. However, this increase in the risk is relatively low when comparing the absolute financing gap of 80 € /kW with the standard deviation of 5 € /kW. As a result, investors should prioritize lowering the fixed and annuity costs over reducing the risk resulting from short-term dispatch decisions. Note that this calculation only holds for representative years regarding RE feed-in and electricity market prices based on the historical observations. In the mid-term, increasing resource prices and additional renewable generation may increase the steepness at both ends of the price duration curve. For electrolysers, particularly the changes in the parts of the price-duration curve below the break-even price are relevant. Thus, price changes due to additional renewable generation allow electrolysers to enhance their economic viability. In the long-term, the expansion of electrolyzer capacity and flexible consumers, in general, may lead to more elastic demand and hence to increased competition for low electricity prices, which could dampen the profitability of electrolysers (see e.g., Lynch et al. (2019), Roach and Meeus (2020), Ruhnau (2021)).

2.6. Conclusions

The hydrogen market ramp-up requires large-scale investments in electricity-based hydrogen production. With substantial subsidies, policymakers aim to set sufficient incentives for investors to realize these investments. As the reduction of CO_2 remains the goal, introducing specific rules for the dispatch along with the investment subsidies is discussed to limit associated emissions from an electrolyzer's energy consumption. One discussed criterion is a simultaneity obligation between renewable energy (RE) generation and electrolyzer production. While its purpose would be to limit the emissions from fossil-fired electricity generation, the measure significantly affects the dispatch of an electrolyzer and may distort the investment incentive.

With our research, we contribute to understanding these distortions that policymakers may consider when designing dispatch criteria for electricity-based hydrogen production. We set up a model framework that allows us to assess a grid-connected electrolyzer dispatch considering the risk from varying RE generation. The variation of RE is captured by a Markov chain Monte Carlo simulation for wind generation. Subsequently, two regression models for the intraday and day-ahead markets are calibrated with historical data from the German spot markets to calculate synthetic electricity spot market price time series. We introduce simultaneity to the dispatch model and evaluate its structural impact on the distribution of the electrolyzer's contribution margin, full load hours, and associated emissions within a case study in the German electricity market context.

In the short term, we show that the introduction of a simultaneity obligation delivers on its original goal of reducing the associated CO_2 emissions from electricity consumption. On the other hand, an absence of simultaneity comes with several significant benefits for the operator of an electrolyzer: the contribution margin and production rate increase while the risk from RE generation decreases.

Hydrogen from RE sources is part of many energy and climate policies since it provides long-term energy storage and is a close substitute to fossil energy carriers. Moreover, hydrogen has also gained interest in economic policy, since substantial economic value in hydrogen trade as an energy commodity and in an emerging market for hydrogen equipment is anticipated. Investing in hydrogen today is essential to commercializing the technology and to achieving long-term learning and scaling effects. The simultaneity obligation is a regulatory measure that concentrates on the short-term decisions of electrolyzer operation, though it also affects investment incentives. Although the effects of a simultaneity obligation on the contribution margin are significant, they are comparatively low in comparison with the total financing gap, i.e., also considering investment cost. With the design of a simultaneity obligation, policymakers are weighing two goals: ramping-up the hydrogen market in the long-term and preventing emissions from the power sector in the short-term. A low simultaneity—or even the absence of such an obligation—favors a more dynamic hydrogen market ramp-up, while a strict simultaneity ensures to mitigate emissions but may lead to less investment. While these effects are immediate results from our analysis, further aspects that need to be considered are the interplay of the simultaneity obligation with other emission abatement measures and the entire energy system, e.g., regarding carbon trading schemes and the long-term transformation of the energy system. Regardless of the actual design of the simultaneity obligation, it has a role to play in future policies addressing green hydrogen since it has a significant impact on the electrolyzer operation.

3. The Shape of U - On the Structure of Utility from Electric Vehicle Charging

3.1. Introduction

Electric vehicle (EV) adoption accelerates. According to IEA (2024) current stated national policies, projections show 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., 2017b). 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.

3.1.1. 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. (2017b) 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. (2017b, 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. (2017b) 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. (2017b).

Several publications attempt to address the gap in modeling EV user charging behavior. Table 3.1 summarizes the key applications of utility functions in EV charging models, highlighting their properties and data sources. A notable contribution is Daina et al. (2017a) 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. (2017a) 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. (2017a), 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.

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

Table 3.1.: 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).

(a) Application and data sources of the utility functions.

Paper	Application	Data		
		EX	SP	RP
Daina et al. (2017a)	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	●		
Theile (2025)	Charging choice			●

(b) Marginal utility properties of the utility functions.

Paper	Marginal utility				
	Time		Energy		Inter.
	Con.	Var.	Con.	Var.	
Daina et al. (2017a)	●		●		
Fridgen et al. (2021)				●	●
Galus et al. (2012)			●		
Liu et al. (2022)			●		
Nourinejad et al. (2016)	●				
Valogianni et al. (2020)				●	
Wang et al. (2021)			●		
Wu et al. (2022)	●				
Xing et al. (2021)	●		●		
Theile (2025)		●		●	●

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).

3.1.2. 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 chapter 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 chapter 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 that (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 3.2 presents the theoretical framework of examining charging choices. In Section 3.3, the empirical model is explained. Section 3.4 sets up the case study, before Section 3.5 shows the results. After discussing the findings in Section 3.6, the chapter concludes in Section 3.7.

3.2. 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.

3.2.1. Choice framework

As a starting point, Daina et al. (2017a) offer an intuitive depiction of the choice space an EV user faces when arriving at a charging station. Following their approach, Figure 3.1 illustrates a general choice space of EV charging options.

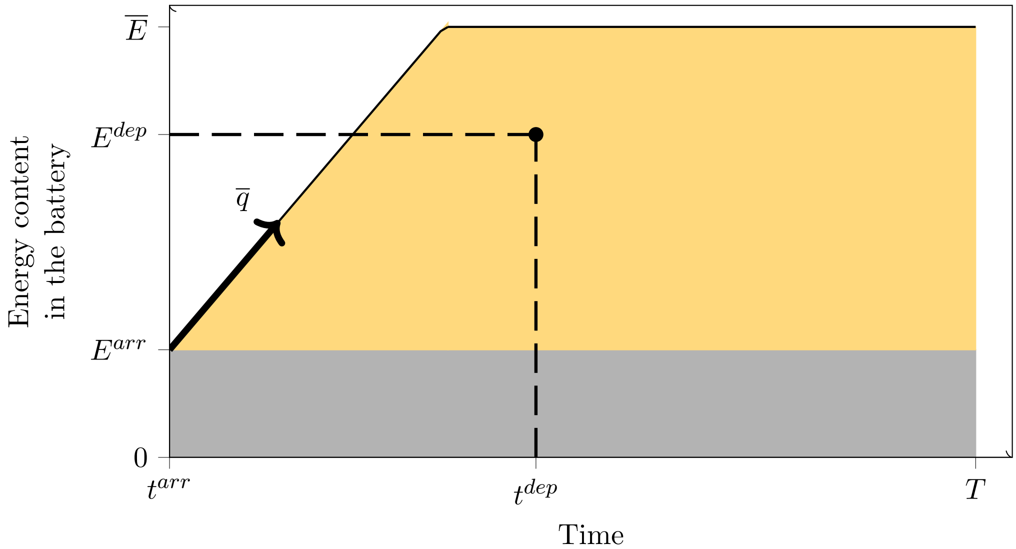

Figure 3.1.: The choice space of an EV user arriving at a charging station from Daina et al. (2017a). The bold bullet marks the chosen alternative at departure energy E^{dep} and departure time t^{dep}. The maximum available charging rate $\overline{q}$ limits the choice space.

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.

3.2.2. 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 3.1.1, 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 (3.1), with β as coefficients of the utility attributes.

$$U^D(E^{dep}, \Delta t, \beta) = \begin{cases} \beta_1 E^{dep} & \text{LiP Energy} \\ \beta_1 \Delta t & \text{LiP Duration} \\ \beta_1 E^{dep} + \beta_2 \Delta t & \text{LiP Energy \& Duration} \\ \beta_1 E^{dep} + \beta_2 \Delta t & \text{QiP Energy \& Duration} \\ +\beta_3 {E^{dep}}^2 + \beta_4 \Delta t^2 & \\ \beta_1 E^{dep} + \beta_2 \Delta t & \text{QiP Interaction} \\ +\beta_3 {E^{dep}}^2 + \beta_4 \Delta t^2 & \\ +\beta_5 E^{dep} \Delta t & \end{cases} \tag{3.1}$$

Figure 3.2 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.

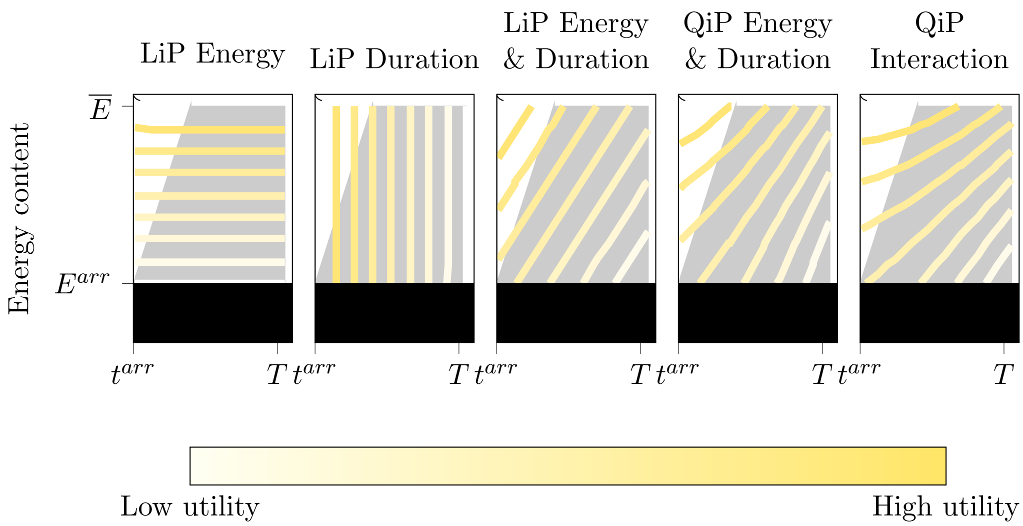

Figure 3.2.: Isoquants of the five utility functions (in yellow), over a shared product space (in grey). The utility functions are either linear-in-parameter (LiP) or quadratic-in-parameter (QiP) and include different combinations of charging product attributes energy and duration.

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 (3.2), with γ as coefficient of the product costs.

$$U^N(E^{dep}, \Delta t, C, \beta, \gamma) = U^D(E^{dep}, \Delta t, \beta) + \gamma C \tag{3.2}$$

3.3. Empirical model

Against the background of the decision framework presented in Section 3.2, this section presents an empirical model that allows to estimate the coefficients of different utility functions.

3.3.1. Discrete choice model estimation

This chapter 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 (3.3) (Berbeglia et al., 2022).

$$U^R_{s,j} = U^N_{s,j}(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j}, \beta, \gamma) + \epsilon_{s,j} \tag{3.3}$$

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 (3.4a). 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 (3.4b) defines the probability of choosing an alternative j in the MMNL model, where any density function can be assumed for f.

$$\mathcal{P}(j|J) = \frac{e^{U^N_j}}{\sum_{i \in J} e^{U^N_i}} \tag{3.4a}$$

$$\mathcal{P}(j|J) = \int \frac{e^{u^N_j}}{\sum_{i \in S} e^{u^N_i}} f(u^N|\theta) du^N \tag{3.4b}$$

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 (3.5) 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}.

$$\mathcal{L}_{\mathcal{U},\mathcal{M}} = \prod_{s}^{S^{in}} \mathcal{P}_{\mathcal{U},\mathcal{M}}(j_s^o | J_s, \beta_{\mathcal{U},\mathcal{M}}, \theta_{\mathcal{U},\mathcal{M}}, \gamma_{\mathcal{U},\mathcal{M}}) \tag{3.5}$$

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 (3.6).

$$\max_{\beta,\gamma,\theta} \sum_{s}^{S^{in}} \log \mathcal{P}_{\mathcal{U},\mathcal{M}}(j_s^o | J_s, \beta_{\mathcal{U},\mathcal{M}}, \theta_{\mathcal{U},\mathcal{M}}, \gamma_{\mathcal{U},\mathcal{M}}) \tag{3.6}$$

3.3.2. Metrics

The first question of this chapter 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 (3.7). 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.

$$RMSE(S^{out}, \mathcal{P}_{\mathcal{U},\mathcal{M}}) = \sqrt{\frac{\sum_{s}^{S^{out}} \sum_{j}^{J_s} (I(j = j_s^o) - \mathcal{P}_{\mathcal{M}}(j|J_s))^2}{\sum_{s}^{S^{out}} (|J_s| + 1)}} \tag{3.7}$$

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 $U_{s,j}^{dep}(C_{s,j} + \delta_{s,j}^{C}, X_{s,j} + \delta_{s,j}^{X}) = U_{s,j}^{dep}(C_{s,j}, X_{s,j})$. The travel behavior literature typically examines the *value of time* (Bierlaire, 2017, Train, 2009). This chapter 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 (3.8), while the *value of energy* is derived from equation (3.9).

$$
\begin{aligned}
VoT = \frac{\delta^{C}_{s,j}}{\delta^{\Delta t}_{s,j}} &= \frac{(\delta U^{N}_{s,j}/\delta \Delta t_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})}{(\delta U^{N}_{s,j}/\delta \Delta C_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})} \\
&= \begin{cases} \frac{\beta_2}{\gamma} & \text{LiP Energy \& Duration} \\ \frac{\beta_2 + 2\beta_4 \Delta t_{s,j} + \beta_5 E^{dep}_{s,j}}{\gamma} & \text{QiP Interaction} \end{cases}
\end{aligned}
\tag{3.8}
$$

$$
\begin{aligned}
VoE = \frac{\delta^{C}_{s,j}}{\delta^{E}_{s,j}} &= \frac{(\delta U^{N}_{s,j}/\delta E^{dep}_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})}{(\delta U^{N}_{s,j}/\delta \Delta C_{s,j})(E^{dep}_{s,j}, \Delta t_{s,j}, C_{s,j})} \\
&= \begin{cases} \frac{\beta_1}{\gamma} & \text{LiP Energy \& Duration} \\ \frac{\beta_1 + 2\beta_3 E^{dep}_{s,j} + \beta_5 \Delta t_{s,j}}{\gamma} & \text{QiP Interaction} \end{cases}
\end{aligned}
\tag{3.9}
$$

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 (3.10). 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.

$$
R^{Total}_{m} = \sum_{s}^{S^m} \sum_{j}^{J_s} P(j|J_s) C_{s,j} \tag{3.10}
$$

3.4. 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.

3.4.1. 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.2.1 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 B.3.1 presents sensitivities of the model results on the number of observations and the number of alternatives included in the choice set. Appendix B.3.2 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.2.2 describes in detail the imputations performed to enrich and curate the data for the case study. Table 3.2 summarizes the key assumptions made.

Table 3.2.: 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	B.2.5
Blocking fee	P^{Block}	€ /min	0.1	B.2.5
Maximum paid blocking time	$\bar{t}^{Block}$	€	12	B.2.5
Charging losses		%	15	ADAC (2022)
Minimum state of charge at arrival	$\underline{E}^{arr}$	%	10	Own assumption
Time resolution	δt	min	60	Own assumption

3.4.2. 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 3.2.1, practical constraints at public charging stations restrict the actual choices observed in the case study dataset. The derivation of this chapter's choice 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 3.3 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

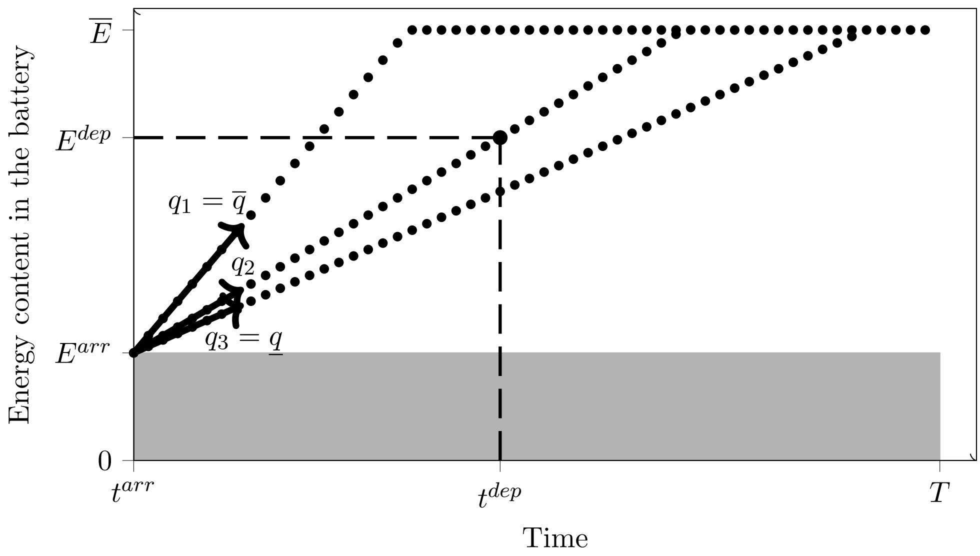

Figure 3.3.: The discrete choice set of an EV user arriving at a charging station based on Daina et al. (2017a). The bullets mark alternatives in the choice set, with the bold bullet marking the chosen alternative at departure energy E^{dep} and departure time t^{dep}. The set of available charging rates 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.

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 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 $\min\limits_{s \in S} E^{arr}$ is set to zero, as expressed in equation (3.11).

$$U^N_{s,0}(\min_{s \in S} E^{arr}, 0, 0, \beta, \gamma) = 0 \tag{3.11}$$

3.4.3. Choice and station description

By constructing the choice sets according to the approach described in Section 3.4.2, 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 3.4 depicts the distribution of the three product attributes charged energy, duration, and price paid.

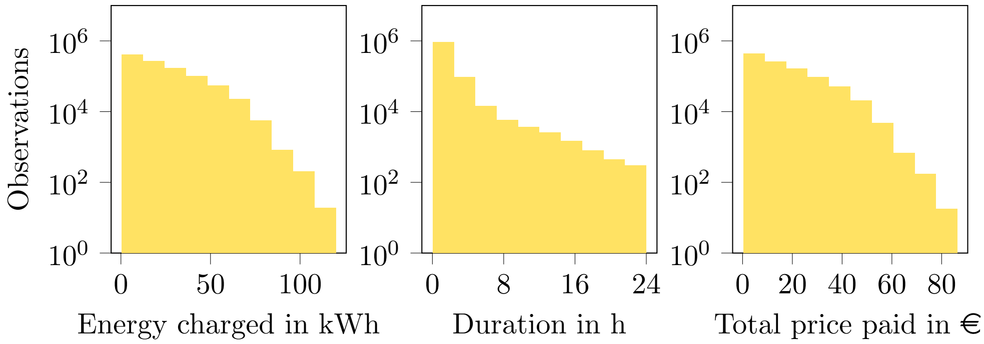

Figure 3.4.: The distribution of the energy charged, duration, and total price paid of the chosen products in the dataset of 1.03 mio. charging sessions reported for 2023 at 1,145 charging stations with varying charging rates based on (NCfCI, 2024) and the assumptions in 3.4.1.

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 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 3.5 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 €.

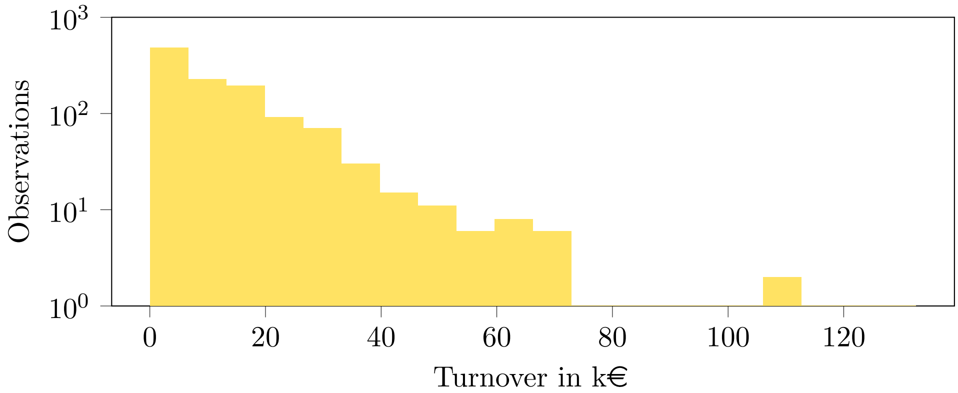

Figure 3.5.: The distribution of the total turnover in 2023 at 1,145 charging stations with varying charging rates based on (NCfCI, 2024) and the assumption in 3.4.1.

3.5. 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.

3.5.1. Utility function comparison by model-fit

To answer the first question, the coefficients of each of the five utility functions from Section 3.2.2 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 3.6 illustrates the RMSE of the models applied to the out-of-sample set.

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 a slightly improved fit in the MMNL case, suggesting that while connection time explains much of the observed behavior, energy content contributes significantly.

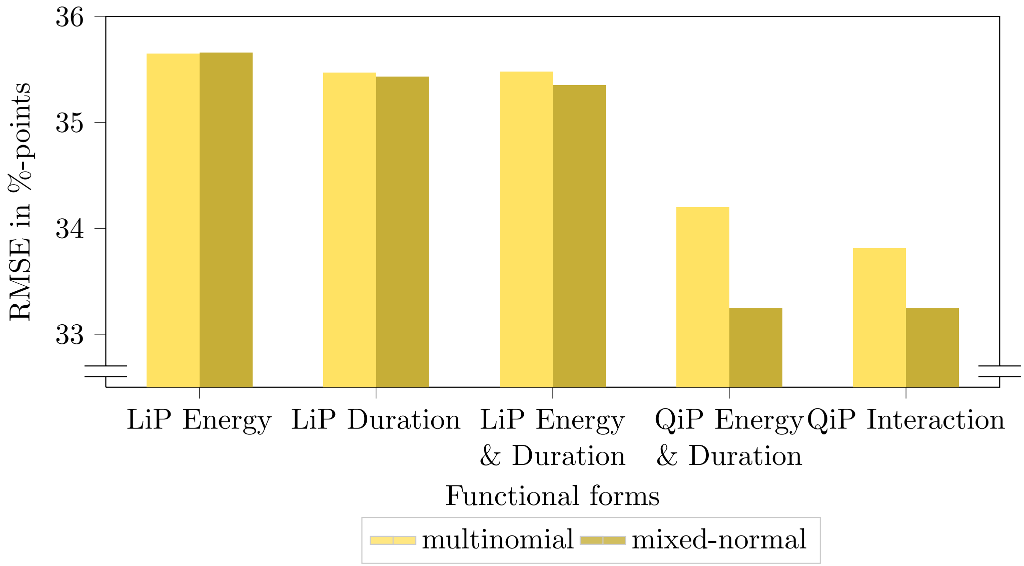

Figure 3.6.: The Root Mean Square Error of the five utility functions under a multinomial logit and a mixed multinomial logit discrete choice model. The RMSE is computed on an out-of-sample dataset of 2,000 observations.

The 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 3.2.2, it may not fully reflect an EV user's decision rationale. 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, Section 3.5.2 presents the estimated coefficients.

The MNL and the MMNL with normally 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 3.5.5 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.

3.5.2. Utility function comparison by estimated coefficients

Examining the actual coefficients of the estimated utility functions answers the second research question of this chapter. The model improvement by incorporating parameters allowing for non-linear forms of utility in Section 3.5.1 suggests that the quadratic and interaction terms explain some share of the variation in the observed charging choices. Table 3.3 lists the estimated coefficients for each of the five utility function specifications under the MNL model.

Table 3.3.: 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., 2017a). 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 B.3. Appendix B.3.3 explores potential model extensions using specific constants, while Appendix B.3.4 investigates the correlation between the higher-order utility function variables.

3.5.3. 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 3.7 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.

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

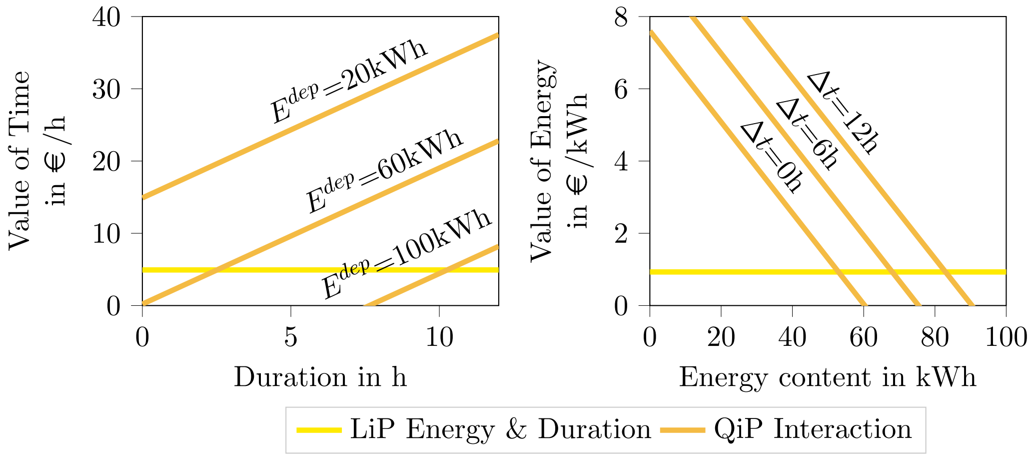

Figure 3.7.: The value of time over the duration of the charging product and the value of energy over the energy content in the battery at departure for the utility functions *LiP Energy & Duration* and *QiP Interaction*.

station earlier, negative values suggest a willingness to pay for staying longer. As outlined in Section 3.1.1, 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 3.5.5 further explores preference heterogeneity by examining different charging station segments and times.

3.5.4. 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*. Tables 3.4 and 3.5 show the resulting coefficients.

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.2.1), where multiple downstream charging options are available.

Table 3.4.: 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*.

(a) Columns (1) to (5) for segmentations *Area* and *Activity*.

	(1)	(2)	(3)	(4)	(5)
	Area			Activity	
	Rural	Sub-Urban	Urban	Parking	Refueling
Costs	-0.062***	-0.057***	-0.050***	-0.052***	-0.110***
	(0.009)	(0.019)	(0.019)	(0.004)	(0.015)
Energy	0.567***	0.502***	0.462***	0.463***	0.822***
	(0.029)	(0.060)	(0.062)	(0.011)	(0.051)
Duration	-1.513***	-1.249***	-1.041**	-1.104***	-2.806***
	(0.223)	(0.462)	(0.472)	(0.088)	(0.456)
Energy^2	-0.005***	-0.004***	-0.004***	-0.004***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Duration^2	-0.009	-0.056**	-0.068***	-0.060***	0.002
	(0.010)	(0.022)	(0.023)	(0.006)	(0.028)
Interaction	0.020***	0.021***	0.019***	0.019***	0.035***
	(0.004)	(0.007)	(0.008)	(0.001)	(0.007)
Observations	1193	4459	2348	7012	988

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

(b) Columns (6) to (7) for segmentation *Charger*.

	(6)	(7)
	Charger	
	AC	DC
Costs	-0.055***	-0.075***
	(0.008)	(0.016)
Energy	0.341***	0.532***
	(0.024)	(0.049)
Duration	-0.301**	-1.395***
	(0.131)	(0.285)
Energy^2	-0.003***	-0.004***
	(0.000)	(0.000)
Duration^2	-0.103***	-0.052***
	(0.008)	(0.020)
Interaction	0.018***	0.018***
	(0.002)	(0.005)
Observations	2673	5327

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

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 3.1.1, 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.2.1), 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.

Table 3.5.: 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.

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 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.

3.5.5. 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 3.8.

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

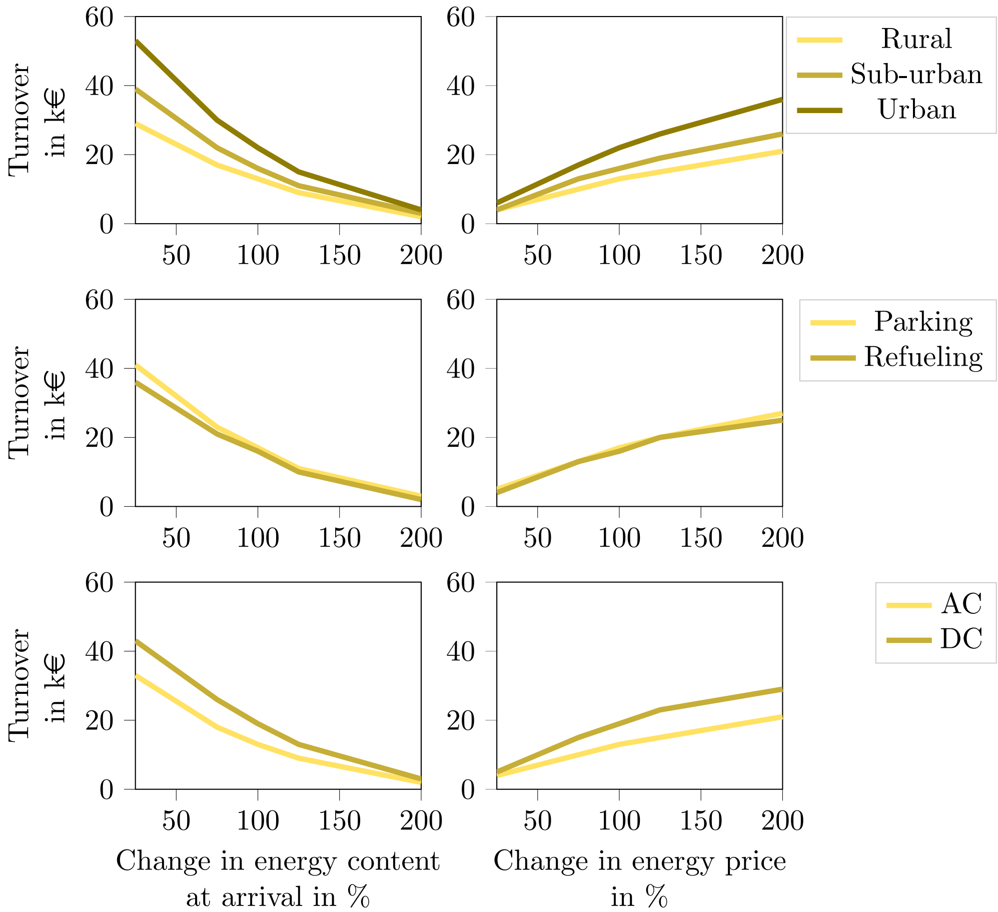

Figure 3.8.: The mean of the total turnover over all charging stations in a single segment, depending on the decision margins relative to the arrival SoC and the energy price.

energy 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 3.5.5. 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.

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.

3.6. 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.

3.6.1. 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. (2017a). 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 chapter reveals increasing marginal disutility regarding the duration of a session. Typically, models such as Daina et al. (2017a) 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.

3.6.2. 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 analyses 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 suggest that the flexibility may be more constrained than modeled. 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.

3.6.3. 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 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 B.3.4 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).

3.7. Conclusion

This chapter 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 chapter 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 chapter 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 chapter 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.

4. Environmental policy instruments for investments in backstop technologies under present bias - an application to the building sector

4.1. Introduction

4.1.1. Background and motivation

Governments of many countries have set themselves climate targets, i.e., emission reduction targets. These targets no longer aim at a mere partial reduction of greenhouse gas (GHG) emissions, but rather at a reduction of GHG emissions to zero or close to zero. More than 70 countries pledged to reach net-zero emissions, including the countries of the European Union, China, and the USA (United Nations, 2023). Investments must be stimulated and carried out beyond efficiency improvements to achieve these goals. Therefore, in all sectors, investments in zero-emission technologies, i.e., backstop technologies, must be made.[8] A backstop technology is a process or a technology in which the use of an exhaustible resource can be completely avoided. In this chapter, we define backstop technology more narrowly: as a technology that does not emit CO_2 during operation. We assume that such a technology exists at finite cost.[9]

An example is the residential building sector: Global GHG emissions from building operations, i.e., heating and hot water provision, have increased in recent years. In 2021, global direct CO_2 emissions from building operations accounted for around 8 % of global energy-related CO_2 emissions (IEA, 2022). In the residential building sector, decarbonization needs to be carried out by private households investing in new technologies (e.g., heating systems and refurbishment) and choosing their indoor temperature level. In this chapter, the analysis is applied to the residential building sector, although the results are generalizable.

The prominent policy from classic economics to reach the first-best outcome in the presence of an environmental externality (i.e., the emitted emissions) is to introduce a price on said externality (i.e., a carbon or CO_2 price), internalizing the externality into the decision-making rationale of the households, like the

[8] Alternatively or additionally, hard-to-avoid emissions can be offset by natural or technical carbon sinks.

[9] More details in Section 4.2.

Pigouvian tax (Pigou, 1920). Empirical literature suggests that individuals do not always behave according to classic rational choice theory. Behavioral issues, such as time-inconsistent discounting (e.g., present bias), could prevent individuals from investing optimally in time. Heutel (2015) has shown that if consumers experience present bias, a Pigouvian tax does not lead to welfare optimal investment decisions for externality-producing durable goods. Instead, the optimal policy mix consists of an instrument to correct the externality and another one aiming at the present bias, constituting an internality. Besides carbon taxation or pricing, these instruments can include subsidies, taxes based on efficiency, or mandates.

In his analysis, Heutel (2015) assumes that consumers can invest in technologies with different efficiencies. Sheer improvement of efficiencies in externality-producing durable goods, however, cannot reduce externalities to zero. Thus, by assumption, no backstop technology exists. The author finds that there is a welfare-optimal amount of externalities (i.e., GHG emissions) corresponding to the Pigouvian tax rate, which represents the monetary damage of the externality. The optimal level balances the damage from the externality with the utility derived from the externality-producing good. In contrast, in many countries, the declared political target is to achieve zero or close to zero emissions.[10] The implicit assumption when applying a zero-emission target is, that the marginal damage from GHG emissions is higher than corresponding marginal abatement costs, and correspondingly, the optimal amount of GHG emissions is zero. Put differently, the policy maker is interested in target-consistent CO_2 pricing and policy measures rather than taxing the externality at the rate of social costs of carbon (Aldy et al., 2021).

Building on the work of Heutel (2015), this raises the following questions. First: How can Heutel's model be generalized to account for the existence of zero emission backstop technologies with finite costs? Second: What does this generalization imply for the main propositions of the model? Third: What are optimal policies under present bias for externality-producing durable goods if the optimal investment decision is the investment in the backstop technology?

We generalize the analytical model of Heutel (2015) for investments in externality-producing durable goods under present bias by allowing for a greater technology space. In the generalized model, the investment may be accompanied by the substitution of the fuel used, for example, in the case of heating investments, switching from a gas heating system to an electric heat pump. The integration of fuel substitution into the investment decision allows us to depict the existence of a zero emissions backstop technology.

We first examine the effect of the model generalization on Heutel's main propositions, assuming still that there is a welfare-optimal inner solution, i.e., that the

[10] In the following, we abstract from the possibility of carbon sinks to achieve net-zero targets and assume that the goal of the investments under investigation is to reduce emissions to zero.

backstop technology is not optimal. We then discuss the implications of the situation when the investment in the backstop technology is optimal. This may be the case if the assumed damage of the externality is high enough so that the backstop technology is welfare-optimal, or due to politically set zero-emission targets. In a stylized case study for a representative building of the German building sector, we assume a politically set zero-emission target. We numerically estimate real-world magnitudes of the present bias effect on heating-related investment and utilization decisions, emissions, policies, and associated deadweight loss.

In our analysis, we show that as long as social damage of carbon and the corresponding CO_2 price is not high enough to make the backstop technology optimal, households in the optimum will still emit CO_2. In this case, Heutel's propositions hold that to reach the social optimum, we need two policy instruments, one to address the internality and a second one to address the externality. Generalizing Heutel's propositions, if the social costs of carbon and the corresponding CO_2 price are high enough, a mark-up on the CO_2 price can also induce the social optimum. Therefore, present bias can be addressed by a tax or another single instrument when aiming at zero emissions in the presence of a zero-emission backstop technology. In numerical simulations for a representative household in Germany and under the assumption of continuous investment choices, we quantify the target-consistent CO_2 price for reaching zero-emissions without present bias at 192€/tCO_2. Applying this target-consistent CO_2 price in the case of present bias leads to a welfare loss. In the case of a present-biased household, a higher CO_2 tax exists that reaches the target (in our exemplary building and an assumed present bias of 0.7: 235€/tCO_2 including an internality-mark-up of 43€/tCO_2). While the optimal tax rate and subsidy depend on the level of present bias, we find that there exists an optimal tax-subsidy combination that is optimal regardless of the level of present bias.

4.1.2. Related literature and contribution

Ever since (Strotz, 1955) introduced the idea of time-inconsistent discounting with his theory of commitment, it has been recognized that consumers may deviate from the assumption of exponential, thus time-consistent, discounting.[11] In line with time-inconsistent discounting, Laibson (1997) coined the concept of present bias, i.e., agents' preference for immediate benefits over advantages in future periods beyond exponential discounting.[12] To represent this behavior, the literature has introduced and applied models of quasi-hyperbolic discounting (Laibson, 1997, O'Donoghue and Rabin, 1999, Phelps and Pollak, 1968).

[11] Frederick et al. (2002) includes a critical review of the history and models of time discounting, including time-consistent utility discounting models as well as time preferences and (quasi-)hyperbolic discounting models.

[12] See the reviews Frederick et al. (2002) and DellaVigna (2009) for empirical estimates for present bias in various circumstances and Imai et al. (2021) and Cheung et al. (2021) for recent meta studies of papers reporting present bias estimates.

One metric for policy evaluation is welfare. Assuming time-inconsistent preferences implies that preferences change over time, complicating welfare analysis. Economists provide several welfare criteria to overcome this complication. The two most prominent criteria are the Pareto criterion, i.e., considering each period's perspective in overall utility, and the long-run criterion, i.e., evaluating the "true" utility from a long-run perspective (O'Donoghue and Rabin, 2015). O'Donoghue and Rabin (1999) argue that the Pareto criterion is too strong an assumption when applied to intertemporal choice. O'Donoghue and Rabin (2015) claim that both approaches, as well as other thinkable welfare criteria, frequently yield the same conclusions but argue for the usage of the long-run criterion.[13] As Heutel (2015) utilizes the long-run criterion in his model, we will also apply it.

Applying the long-run criterion deviates from standard social welfare analysis, which relies on revealed preferences as information about the consumer's true utility. The paternalistic assumption that the consumer's choices do not optimize her welfare is as critical as it is controversial. Gilles Saint-Paul (2011) argues that taxes levied for inducing a particular behavior might only lead to consumers paying higher prices instead of changing behavior, reducing overall welfare. According to Whitman (2006), the justifications of policy interventions for addressing internalities are based on the idea of Pigouvian taxation, ignoring Coase's theorem (R. H. Coase, 1400). The theorem states that externalities can be resolved by negotiation between individual parties when transaction costs are low. Since internalities consist of choices within the individual, Whitman (2006) argues that Coase's theorem is better suited for dealing with internalities. The information required to find the least costly option addressing the damage from time-inconsistent discounting is only available to the individual. Moreover, Per Krusell et al. (2002) argues that to tackle consumers' time-inconsistent preferences, only an intervention by a time-consistent social planner is welfare enhancing. Time-consistency of social planners could partly be achieved by avoiding short-term political pressure by establishing credible rules and institutions, enforcing commitment. Examples of such institutions are independent central banks, fiscal rules, and social security systems with automatic adjustments based on demographic or economic changes.

We apply our analysis to the case of households' heating system investment decisions. The empirical literature regarding behavioral biases in energy efficiency decision-making is limited (Gillingham et al., 2009). Schleich et al. (2019) investigated the role of present bias and other behavioral aspects in adopting energy-efficient technologies within different countries in the European Union. They provide evidence for the significance of present bias in reducing investments in energy-efficient appliances and building retrofitting. Werthschulte and Löschel (2021) find that present bias increases power consumption. Therefore, as households undervalue energy costs, price-based policies might fail to reduce

[13]Kang (2015) shows that improvements in the Pareto criterion are also welfare-improving from the long-run perspective.

household energy consumption. Furthermore, in the specific case of investment in household appliances in India, Franz Fuerst and Ramandeep Singh (2018) find that present bias becomes more significant the larger the purchase object investigated. This finding is relevant to our work, as heating system replacement represents a particularly large investment decision for households. Overall, there is not yet a comprehensive empirical view on the effect of present bias on heating system investments. We account for this lack of estimates by considering a range of present bias factors in our numerical simulation.

This chapter focuses on the consequence of present bias in agents' decision-making on policies for decarbonization. The model from Heutel (2015) constitutes the basis of our analysis. A detailed description of the model for analyzing optimal policy instruments for externality-producing durable goods under present bias can be found in Section 4.2.1. Heutel (2015) considers a technology space with efficiency and investment costs as dimensions. We expand this space by allowing technologies to differ in emission intensity and fuel price. As we will see, this generalization enables us to discuss the subject of zero-emission backstop technologies. Other researchers have also addressed the question of how to design policy with externalities and internalities such as present bias (Alcott et al., 2012, Allcott and Sunstein, 2015). Allcott and Sunstein (2015) discuss principles for regulating internalities in the field of energy. They find that internalities such as present bias can justify government intervention, given that "true preferences" of individuals can be identified in contrast to revealed preferences. Alcott et al. (2012) find that when households undervalue long-term energy costs in their investment decisions for durable goods, an externality tax such as a GHG tax yields a double dividend, since it also addresses the internality. They also find, that optimal policy mixes addressing both externalities and internalities depend on unknown information about levels of internalities, private to households. Our results deviate from this finding due to the presence of a zero-emission backstop technology. Since Heutel (2015), recent work has deepened the understanding of present bias in economic policy design and welfare analysis (Bar-Gill and Hayashi, 2021, Chan and Globus-Harris, 2023, Drugeon and Wigniolle, 2021, Kang, 2022, Kotsogiannis and Schwager, 2022, Lades et al., 2021). Bar-Gill and Hayashi (2021) discuss the investment decisions for durable goods by present-biased agents. In contrast to our work, they focus on the effect of purchase financing. They find countervailing effects of present bias on the valuing of the benefits of an investment and the costs of financing said investment and derive recommendations for credit regulation. Since they discuss general durable goods, they do not consider the emission externalities from using energy technologies. Lades et al. (2021) examine investments from present-biased households in energy efficiency technologies. They illustrate particularly how administrative burden can reduce these investments. Similar to our work, they apply a theoretical model and a simulation with exemplary building data. Chan and Globus-Harris (2023) discuss incentivization of energy-efficient appliances such as air conditioners and refrigerators. They find that efficiency incentives on their own, such as subsidies, do not directly address externalities and thus distort consumer decision-making. They show that under certain circumstances, efficiency subsidies may lead to more energy use overall due to the rebound effect. As we will see, our key point of departure from Heutel (2015), Lades et al. (2021) and Chan and Globus-Harris (2023) is that we consider policies reaching zero emissions combined with the availability of a backstop technology.

While there is literature on policies in the context of present bias, to the best of our knowledge, there is no literature addressing the subject of policies for externality-producing durable goods aiming at zero emissions. In the present work, we aim to close this gap by (i) generalizing the model from Heutel to more complex technologies also differing in emission intensity and fuel price to be able to account for zero emission backstop technologies, (ii) analyzing the consequences of the existence of an optimal backstop technology, and (iii) illustrating the consequence of such policies in the residential building sector numerically.

The remainder of this chapter is structured as follows: Section 4.2 gives an overview of the analytical model that serves as the starting point for our analysis. There, propositions resulting from the analytical model are derived regarding the political-economic conditions and low heat demand elasticities in the building sector. Section 4.3 introduces the numerical simulation, assessing findings from section 4.2 numerically and drawing further conclusions. Section 4.4 discusses these results against the background of politically set climate neutrality targets and welfare implications. Section 4.5 concludes this chapter.

4.2. Analytical model

In this section, we first describe the representative agent model for investments in externality-producing durable goods under present bias from Heutel (2015). Then we generalize the model and apply it to the building sector. By defining a larger technology set, we can represent technologies running on different fuels and thus zero emission backstop technologies. Based on the generalized model, we discuss two different cases: first, the case that the backstop technology is not optimal. Second, the case that the backstop technology is the optimal technology choice.

4.2.1. A representative agent model for investments in externality-producing durable goods under present bias

Heutel (2015) describes the investment and operation problem for externality-producing durable goods under present bias in a representative agent model. We present the model based on nomenclature for residential heating. The investment decision is made in the initial period ($t = 0$) and the good lasts T periods. In each period after the investment ($t = 1$ through $t = T$), the household decides on the operating intensity of the good: the generated heat or indoor temperature.

The model is defined by the household's problem and the social planner's problem. In the household's problem, future utility and costs are discounted using quasi-hyperbolic discounting. Quasi-hyperbolic discounting is a method for modeling the behavior of households who experience present bias, i.e., prefer immediate payoffs and undervalue future costs and payoffs.[14] To this end, two discount factors are introduced. δ is called the "long-run" discount factor, and β represents the "present bias". If a household experiences present bias, then $\beta < 1$.

The present-biased household perspective is contrasted with the social planner's problem. Present bias is a behavioral anomaly that a social planner does not experience due to fully rational behavior. One way to solve the social planner's optimization problem is to directly apply the long-run criterion while disregarding the household's present bias, i.e., setting $\beta = 1$. The approach assumes that the household's utility maximization deviates from optimal welfare even from the household's perspective. Thus, the household "makes a mistake" and does not optimize its "true utility".[15]

In the initial period, the household chooses the heating system's ratio of fuel input and generated heat, the so-called effort coefficient fph (fuel per heat), representing the investment decision for the durable good. In the subsequent periods, the heat generated in each period $h_t(t)$ is chosen, which translates into indoor temperature. $U(h_t)$, where $U' > 0$ and $U'' < 0$, describes the utility from generated heat in monetary terms. The costs per kWh of fuel are calculated as the sum of the time-dependent fuel cost (p_t) and a tax per kWh of fuel (τ_t). This fuel tax, hereinafter referred to as the carbon tax, is intended to put a price on the GHG emissions. When choosing a level of fph, the household faces investment costs of $c(fph)$. It is assumed that $c' < 0$, meaning that less efficient goods (heating systems) are less expensive, and $c'' > 0$. The household's problem is thus described in equation (4.1):

$$\max_{fph,\{h_t\}_{t=1}^{T}} \; -c(fph) + \beta \cdot \left[\sum_{t=1}^{T} \delta^t \cdot \Big[U(h_t) - [p_t + \tau_t] \cdot fph \cdot h_t \Big] \right] \tag{4.1}$$

The social planner's problem is characterized by including the externality of fuel consumption. The external damage from fuel consumption, i.e., damage

[14] Technically speaking, present-biased households discount utility and costs in the near future at a higher implicit discount rate than in the distant future (Laibson, 1997).

[15] Alternative welfare criteria in the case of time-inconsistent discounting include the Paretian approach (e.g. Bhattacharya and Lakdawalla (2004)), or the "dictatorship of the present" approach discussed in Jonathan Gruber and Botond Köszegi (2004) or Laibson (1997), which prioritizes the preferences of the current self over the preferences of all future selves. Analogous to the approach in Heutel's basic model and following the arguments of O'Donoghue and Rabin (1999), we apply the long-run criterion.

from GHG emissions, depends on h_t, the kWh of fuel used in each period t, times fph, the fuel used for producing the heat. The damage is denoted as $d(h_t \cdot fph)$, where $d(0) = 0$, $d' > 0$ and $d'' = 0$. The corresponding social planner's problem, using the long-run criterion for discounting and including external damages, is described in equation (4.2):

$$\max_{fph,\{h_t\}_{t=1}^{T}} -c(fph) + \sum_{t=1}^{T} \delta^t \cdot [U(h_t) - p_t \cdot fph \cdot h_t - d(h_t \cdot fph)] \tag{4.2}$$

4.2.2. Model generalization

In the model described in the previous section, consumers invest in one technology and can decide on its efficiency. By assumption, no backstop technology exists because efficiency improvements cannot reduce externalities to zero, and fuel cost differences between technologies used are neglected. We extend the technology set by allowing technologies to run on different fuels. Therefore, the investment decision affects fuel costs and GHG emissions per unit of generated heat. This enables us to analyze how optimal investment decisions depend on fuel cost ratios and to include a zero emission backstop technology. An example of a zero emission backstop technology in the building sector would be the switch to renewably generated heat from solar thermal energy or to electric heating powered by renewably generated electricity.

By allowing technologies to vary in fuel price and emission intensity (down to zero), we extend the technology set and generalize the model. In this generalized model, the fuel price $p_t(fph)$ and the CO_2 factor of the heating system $epf(fph)$ are represented as functions of the effort coefficient fph.[16] The functional form of $p_t(fph)$ is ambiguous: it is conceivable that the change to a more efficient heating system, e.g., from a gas boiler to an electric heat pump, is accompanied by decreasing fuel prices, in € per kWh_{fuel}, but also that the fuel price increases, if, for example, electricity is more expensive than gas.[17] We incorporate a backstop technology with finite costs fph^{BS} by assuming that the emission function $epf(fph)$ equals zero for all $fph <= fph^{BS}$, and $epf' > 0$ for $fph >= fph^{BS}$. This means that when investing in the reduction of fph, $epf(fph)$ decreases linearly until the backstop technology fph^{BS} is reached, where emission intensity is zero. Further investments in reducing fph cannot further reduce the emission intensity.

[16] We model the choice of fph, the investment costs, the change in fuel price, and CO_2 factor as continuous. This serves the theoretical tractability of the model.

[17] By including $p_t(fph)$ as a continuous function, we do not consider explicitly the case of a backstop-technology without fuel costs ($p_t(fph)$ equals zero for all $fph <= fph^{BS}$). An example of that could be self-sufficiency using solar energy. The results of our analysis apply for that case as well.

The household's problem, including quasi-hyperbolic discounting as defined in Section 4.2.1, is thus described as follows[18]:

$$\begin{aligned}\max_{fph,\{h_t\}_{t=1}^{T}} \quad & - c(fph) \\ & + \beta \cdot \left[\sum_{t=1}^{T} \delta^t \cdot \Big[U(h_t) - [p_t(fph) + epf(fph) \cdot \tau_t] \cdot fph \cdot h_t \Big] \right]\end{aligned} \tag{4.3}$$

The household's problem differs from Heutel (2015), since the investment decision fph depends on p_t and the newly introduced CO_2 factor epf. This yields first-order conditions for fph and each h_t. Assume that there exists a unique interior solution.[19] The solutions to the household's problem are called fph^* and h_t^*.

$$\begin{aligned} & - c'(fph^*) \\ & - \beta \cdot \sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot [p_t(fph^*) + epf(fph^*) \cdot \tau_t] \\ & - \beta \cdot \sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot \big[[p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^* \big] = 0 \end{aligned} \tag{4.4}$$

$$U'(h_t^*) - [p_t(fph^*) + epf(fph^*)\tau_t] \cdot fph^* = 0, \forall t \tag{4.5}$$

In equation 4.4, considering the negative sign, the first term $-c'(fph^*)$ is positive. The term represents the benefit of a marginal increase in fph. Since $c' > 0$, it is cheaper to choose a system with higher fph and hence, lower efficiency. Similar to Heutel (2015), the first sum represents the discounted cost of a marginal increase in fph due to the decrease in efficiency: the utility in each future period decreases as heating costs increase. The second sum adds the changes in fuel prices $p_t'(fph)$ and changes in emission costs $epf'(fph) \cdot \tau_t$. While epf_t' is positive, p_t' can be positive or negative, depending on the constellation of fuel prices.[20] If both $p_t'(fph) = 0$ and $epf'(fph) = 0$, the third summand equals zero. In this case, neither the fuel price nor the emission intensity of the heating system depends on the investment decision, obtaining Heutel's application with a limited technology set. Equation 4.5 sets equal the marginal increase in utility of an additional kWh of heat with the marginal increase in costs for each period t.

The social planner's problem uses the long-run criterion and omits the term β. The external damage d depends on the GHG emissions emitted, which are

[18]Appendix C.1 shows the isocost curves of the household's decision problem for illustration.

[19]It is assumed that $\lim_{h_t \to 0} U'(h_t) = \infty$ to ensure a unique interior solution.

[20]We will discuss the implications of this relationship under Proposition 2.

calculated as the product of the emission intensity, the system efficiency, and the provided heat: $d(epf(fph) \cdot fph \cdot h_t)$, where $d(0) = 0$, $d' > 0$ and $d'' = 0$.

The social planner's problem is:

$$\begin{aligned} \max_{fph, \{h_t\}_{t=1}^{T}} \quad & - c(fph) + \Bigg[\sum_{t=1}^{T} \delta^t \\ & \cdot \Big[U(h_t) - [p_t(fph) \cdot fph \cdot h_t] - d(epf(fph) \cdot fph \cdot h_t) \Big] \Bigg] \end{aligned} \tag{4.6}$$

The solutions to the social planner's problem are fph^{opt} and h_t^{opt}. The first-order conditions of the social planner's problem are:

$$\begin{aligned} & - c'(fph^{opt}) \\ & - \sum_{t=1}^{T} \delta^t \cdot h_t^{opt} \cdot \Big[p_t(fph^{opt}) \\ & + epf(fph^{opt}) \cdot d'(epf(fph^{opt}) \cdot fph^{opt} \cdot h_t^{opt}) \Big] \\ & - \sum_{t=1}^{T} \delta^t \cdot h_t^{opt} \cdot \Big[p_t'(fph^{opt}) \\ & + epf'(fph^{opt}) \cdot d'(epf(fph^{opt}) \cdot fph^{opt} \cdot h_t^{opt}) \Big] \\ & \cdot fph^{opt} = 0 \end{aligned} \tag{4.7}$$

$$\begin{aligned} & U'(h_t^{opt}) \\ & - \Big[p_t(fph^{opt}) + epf(fph^{opt}) \cdot d'(epf(fph^{opt}) \cdot fph^{opt} \cdot h_t^{opt}) \Big] \cdot fph^{opt} \\ & = 0, \forall t \end{aligned} \tag{4.8}$$

4.2.3. Analysis

Optimal inner solution

First, we analyze the case that there is a welfare-optimal inner solution, i.e., that the backstop technology is not optimal and $fph^{opt} > fph^{BS}$. This is the case when the assumed external damage from GHG emissions is smaller than necessary for the backstop technology to be welfare-optimal. Thus, there exists a welfare-optimal quantity of GHG emissions that exceeds zero. The optimal solution is therefore found in the non-zero linear part of the emission intensity function $epf(fph)$.

From the first-order conditions of the household and the social planner, it follows that if $\beta = 1$, the household chooses the first-best outcome if $\tau_t =$

$d'(epf(fph^{opt}) \cdot fph^{opt} \cdot h_t^{opt})\ \forall t$. This is the Pigouvian tax rate, called τ_t^{pig}, which internalizes fossil fuel usage's external damage.

As in Heutel (2015), the following holds for the adapted model:

Proposition 1.
Let $\beta < 1$: No set of emissions tax τ_t for all $t\epsilon[1,...,T]$ exists that leads to the first-best outcome fph^{opt} and h_t^{opt}.[21]

If the Pigouvian tax rate is applied, Heutel (2015) obtains that too little is invested and the good is underutilized compared to the optimum of the social planner. In our case, when looking at heating investments, whether too much or too little is invested due to present bias depends on how fuel and emission costs are affected by the investment decision, leading to Proposition 2:

Proposition 2.
Let $\beta < 1$: If $\tau_t = \tau_t^{pig}$ for all $t \in [1,...,T]$ and $\sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot \Big[[p_t(fph^*) + epf(fph^*) \cdot \tau_t] + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^* \Big] \geq 0$ then $fph^* > fph^{opt}$ and $h_t^* < h_t^{opt}$ for all $t \in [1,...,T]$.[22]

Proposition 2 states that present-biased households under-invest in the investment period and heat less than optimal in the subsequent periods, as long as the change in discounted future costs for a marginal increase in fph (marginally less efficient heating system) is greater than or equal to zero. The scenario occurs if $p' >= 0$, meaning that the price for heating increases for less efficient heating systems. Then, the optimal solution is found as the trade-off between fph decreasing investment costs on the one side and the marginal increase in future heating costs consisting of the effects of the decreased efficiency, increasing emission costs, and increasing fuel costs on the other side. In the other scenario, in which $p' < 0$, the described relationship only continues to hold as long as the emission tax and lower efficiency offset the decrease in fuel costs for a marginal increase in fph. If this does not hold, i.e., $p_t' << 0$, a marginal increase in fph leads to lower investment costs and a decrease in future costs. In such a case, it would be optimal to invest as little as possible, thus $fph \to \infty$.

In the case of present bias, no set of CO_2 tax rates produces the first-best outcome regarding investments, fuel usage, and GHG emissions. A second-best policy solely based on CO_2 tax rates must consist of higher tax rates than the Pigouvian tax rate. The tax must address the usage of the heating system while also unfolding high incentives in the investment period, compensating for the present bias. A tax that incentivizes efficient investment despite present

[21]The proof is presented in Appendix C.2.1.
[22]The proof is presented in Appendix C.2.2.

bias cannot be optimal because the tax is too high in subsequent periods to incentivize optimal heating use, given the optimal efficiency level, the utility of heating, and GHG emission damage. A second policy instrument has to be introduced to achieve the first-best result. In Heutel (2015), the author discusses a tax on the goods effort coefficient in the starting period and a fuel effort coefficient standard. In the case of the building sector, there is another policy measure often applied by the regulator: A subsidy on capital expenditures on more energy-efficient or less emission-intensive technologies, like, upfront subsidies on heat-pumps (Rosenow et al., 2022). We define this subsidy as a monetary benefit σ that is scaled with $\frac{1}{fph_{min}-fph_{max}} \cdot fph + \frac{1}{1-\frac{fph_{min}}{fph_{max}}}$. The subsidy thus decreases linearly in fph. The household gets the full value of the subsidy if the household chooses fph_{min} and no subsidy if the household chooses fph_{max}:

Proposition 3.
Let $\beta < 1$: The first best is achieved by setting $\tau_t = \tau_{pig}$ in each period $t > 0$ and setting a capital subsidy in the form of $(\frac{1}{fph_{min}-fph_{max}} \cdot fph + \frac{1}{1-\frac{fph_{min}}{fph_{max}}}) \cdot \sigma$ with $\sigma = (fph_{min} - fph_{max}) \cdot (\beta - 1)$
$\cdot \sum_{t=1}^{T} \delta^t \cdot h_t^{opt} \cdot \big[[p_t(fph^{opt}) + epf(fph^{opt}) \cdot \tau_t^{pig}] + [p_t'(fph^{opt}) + epf'(fph^{opt}) \cdot \tau_t^{pig}] \cdot fph^{opt}\big]$.[23]

Since the household is present-biased, in the investment period, the household only considers a share of β of the future discounted benefits from decreasing fph. The subsidy is therefore composed of the benefit from investing in lower fph, expressed in the sum, times $(\beta-1)$, offsetting the present bias in the investment period. In contrast to the fuel economy tax in Heutel (2015), our model's subsidy depends not only on h_t^{opt} but also on fph^{opt}. The intuition behind this is that due to the fuel switch when investing, fph^{opt} is relevant for determining the marginal benefit from an increase in fph as it defines fuel and emission costs in the optimal case. This means that for the optimal design of the subsidy, it is crucial to know how the optimal investment changes the fuel and emission costs. Besides the level of fuel and emission costs at fph^{opt}, also their slopes at this point determine the optimal subsidy. In contrast to Heutel (2015), marginal changes in investment affect the fuel price and the emission intensity. Therefore, the subsidy accounts for the marginal variable cost changes, composed of fuel price and emission intensity, induced by investment decisions under present bias. The term can both increase or decrease the optimal subsidy, as the fuel price can have a positive or negative slope in fph^{opt}.

Optimal backstop technology

In the model so far, we assumed that there exists a welfare optimal amount of GHG emissions that relates to the Pigouvian tax rate, internalizing the exter-

[23]The proof is presented in Appendix C.2.3.

nal emission damage. It was not optimal to invest in the backstop technology. In contrast, in the current political debate around the decarbonization of the building sector, the declared target is to achieve zero emissions. The implicit assumption is, thus, that the damage from GHG emissions is higher than corresponding abatement costs, and correspondingly, the optimal amount of GHG emissions is zero: fph is optimal if epf is zero. The same applies to a situation where the zero emission backstop technology is optimal due to sufficiently high assumed external emission damage. In the following, we discuss the case that $fph^{opt} = fph^{BS}$.

The backstop technology does not produce emissions while generating heat, i.e., $epf(fph^{BS}) = 0$. Considering the household's decision problem, we can identify a minimum emission tax rate τ_t^{BS} required to induce investments into the backstop technology. In equations (4.4) and (4.5)), we replace fph^* by fph^{BS}, h^* by h^{BS} and $epf(fph^*) = epf(fph^{BS}) = 0$, obtaining the new first order conditions:

$$\begin{aligned} &- c'(fph^{BS}) \\ &- \beta \cdot \sum_{t=1}^{T} \delta^t \cdot h_t^{BS} \cdot [p_t(fph^{BS})] \\ &- \beta \cdot \sum_{t=1}^{T} \delta^t \cdot h_t^{BS} \cdot \left[[p_t'(fph^{BS}) + epf'(fph^{BS}) \cdot \tau_t^{BS}] \cdot fph^{BS} \right] = 0 \end{aligned} \tag{4.9}$$

$$U'(h_t^{BS}) - [p_t(fph^{BS})] \cdot fph^{BS} = 0, \forall t \tag{4.10}$$

Equation (4.10) determines the optimal heating rate with the backstop technology where marginal utility $U'(h_t^{BS})$ and marginal costs $p_t(fph^{BS}) \cdot fph^{BS}$ equal. This operation decision is thus independent of the emission tax rate, in contrast to the case where there is an optimal amount of GHG emissions. This leaves equation (4.9) for determining the minimum emission tax rate τ_t^{BS}. Assuming T = 1 for simplicity, replacing $epf'(fph^{BS}) * fph^{BS}$ by marginal emissions $\Delta em(fph^{BS})$, $p'(fph^{BS}) * fph^{BS}$ by marginal energy costs $\Delta en(fph^{BS})$, and solving equation (4.9) for τ_t^{BS} leads to the following proposition:

Proposition 4.
Let $\beta < 1$, $fph^{opt} = fph^{BS}$, and $T = 1$: First best can be achieved by a GHG tax $\tau_t^{BS} = \frac{-c'(fph^{BS})}{\beta \cdot \delta^t \cdot h_t^* \cdot \Delta em(fph^{BS})} - \frac{p_t(fph^{BS})}{\Delta em(fph^{BS})} - \frac{\Delta en(fph^{BS})}{\Delta em(fph^{BS})}$ leading to investments in the backstop technology without distorting the heating decision.

The tax τ_t^{BS} is the minimal tax rate that induces zero emissions, when the damage of GHG is high enough for the backstop technology to be optimal. The tax rate consists of three terms.

The first term is the marginal investment costs, divided by the level of present bias, the heating decision, and the marginal emissions. The first term, therefore, describes the marginal abatement costs, discounted by the level of present bias. The higher the marginal investment costs (for reducing the fuel intensity of the heating system fph), the higher the tax τ_t^{BS} inducing investment in the backstop technology. Further, τ_t^{BS} increases with the level of present bias β (lower β signifies a higher present bias), following the findings in the previous sections.

The second term describes the impact of the ratio of fuel prices to marginal emissions on τ_t^{BS}. Here, the overall price level of energy fuels matters. Since the second term is negative, if energy prices are low, τ_t^{BS} needs to be higher to incentivize households to invest in efficient heating systems. However, if energy prices are high, the second term reduces τ_t^{BS} since households already have an economic incentive to invest in more efficient heating systems.

The third term represents the marginal change in energy costs relative to emissions. As stated in Section 4.2.2, the derivative of $p(fph)$ can be positive or negative, depending on the price constellations of different energy carriers such as gas and power. Therefore, $\Delta en(fph^{BS})$ and with that, the third term can be positive or negative. For the case where $\Delta en(fph^{BS})$ is negative, the third term becomes positive. In this case, the relation between marginal changes in fuel prices and marginal changes in emissions increases τ_t^{BS}. Since it is costly to switch to the backstop technology, τ_t^{BS} needs to be higher to counter the disincentive stemming from price changes. This effect is more pronounced, the higher the price increase compared to the reduction in emissions. Ultimately, a higher energy cost change with a smaller emission reduction requires a larger emission tax.

In contrast to Proposition 1 in Section 4.2.3, if the backstop technology is the optimal investment choice, a set of emission taxes $\tau_t > \tau_t^{BS}$ can be used to address both the externality and the internality. This is the case because of the added property of the emission function: We can choose taxes high enough for optimal investment, which induces zero emissions. But since $epf(fph^{opt}) = epf(fph^{BS}) = 0$, the taxes do not influence the heating decision of households anymore. That means that any set of taxes high enough to induce investments in zero-emission heating technologies would be optimal since it does not affect heating decisions in the subsequent periods, as the heating decision becomes independent of the tax. This finding is, in principle, unaffected by the presence of present bias. Present bias only increases the minimum level of the taxes, inducing investments in zero-emission heating technologies.

Following that logic, the optimal investment decision can be derived from a set of taxes or a subsidy alone, a combination of both, or a command-and-control policy, i.e., a ban on new investments in conventional technologies. In our stylized model framework, except for the distributional effects of subsidies, there is no difference between those policies regarding the household's welfare, investment, or heating.[24]

4.3. Numerical simulation

In the numerical case study, we estimate real-world magnitudes of the present bias effect on under-investment, under-consumption of thermal energy, over-emissions, and associated deadweight loss. We obtain optimal single instrument magnitudes of CO_2 prices and subsidies representing the internality-mark-ups. Lastly, we show how present bias differentially affects CO_2 prices and subsidies and therefore numerically obtain optimal policy mixes.

4.3.1. Case study set-up

Metric for evaluation of sub-optimal policies

We numerically investigate the effects of present bias under policy measures aimed at reaching the politically set emission target with the help of a two-step procedure. First, excluding present bias internalities, we determine the minimal target-consistent carbon tax rate inducing investments suitable for zero-emission goals, i.e., in the zero-emission backstop technology.[25] In the reference case, this carbon tax rate τ_t^{neu} is 192€ /tCO_2.[26] Second, we use this carbon tax rate as the implied damage to evaluate social welfare and deadweight loss.

Building and system characteristics

The functional form and parametrization of the utility of heating determine the household's choices. Mertesacker (2021) develops a utility function for domestic heating accounting for the properties of the technical heating system and building envelope. He estimates the utility's parameters within a German case study. We utilize this function and its estimated parameters. Equation (4.11) shows the utility function of our household $U(T_t)$ depending on the ideal indoor temperature $\overline{T}_t$ of 21 °C and chosen indoor temperature T_t. The utility function thus reflects the willingness to pay for the heating temperature. γ expresses the marginal utility of indoor temperature. We also refer to γ as *valuation factor* since it expresses the valuation of a specific household for indoor temperature.

[24] See Section 4.4 for a discussion of the distributional effects of different policies.

[25] In our numerical simulation, we define the backstop technology with finite cost as an air-to-water heat pump. This applies under the assumption of continuously zero-emission electricity generation or, in the case of Germany, assuming that emissions from the electricity sector are accounted for in the electricity sector and will decrease to zero in the long term as part of the European emissions trading system.

[26] In the numerical simulation, for simplicity, we assume constant fuel prices over time and utilize the same CO_2 tax rate in each year of the heating system lifetime.

$$U(T_t) = -\gamma \cdot (\overline{T}_t - T_t)^2 \qquad (4.11)$$

We specify the utility function for the case study by defining an example household by its estimated marginal utility of indoor temperature γ, and an ideal indoor temperature. The characteristics and estimates of the corresponding marginal utility from indoor temperature stem from the median household in Mertesacker (2021). For this household, we obtain a γ of 25€ $/\Delta T^2$.[27] Figure 4.1 shows the resulting utility function and variations for the exemplary household.

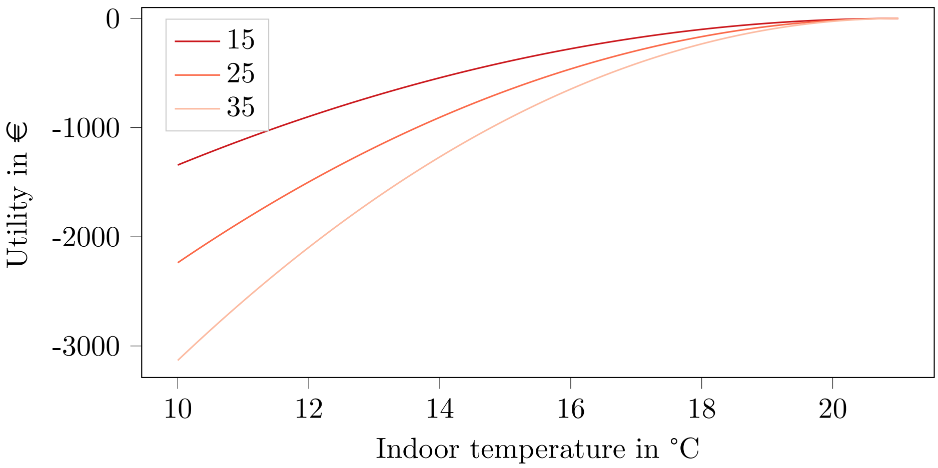

Figure 4.1.: Utility Functions of indoor temperature for varying valuation factors.

The heat demand in the case study, associated with the indoor temperature choice, is based on a representative building from Diefenbach et al. (2015) and IWU (2016). [28] Given the physical building characteristics, IWU (2016) provides heat demands for different indoor temperature levels. For simplification, the calculation aggregates over the entire heating period, taking an average ambient temperature as input. Similarly, the indoor temperature can be interpreted as an average over this heating period. The heat demand, in this case, is the heat demand for one heating period given the chosen average indoor temperature. Such theoretical calculation methods for determining heat demand tend to overpredict the real heat demand (Loga et al., 2012, Mertesacker, 2021). To account for this overprediction, we assume an adaptation factor of 0.8 for our representative building, based on Loga et al. (2012) and IWU (2016). The choice of this factor is consistent with the results of Mertesacker (2021), who estimates lower adaptation factors, but does not take into account domestic hot water generation. The heat demand in our model h [kWh] is then approximated as a

[27] The underlying assumption of the household characteristics, the marginal utility estimates, and the computation of the valuation factor is described in Appendix C.3.1.

[28] Refer to Appendix C.3.2 for a more detailed description of the building, the computation of the heat demand, and the underlying assumptions.

linear function, depending on the chosen temperature T [°C]:

$$h = 0.8 \cdot 147.1\, m^2 \cdot (11.61\, \frac{kWh}{m^2 \cdot ^\circ C} \cdot T - 19.85\, \frac{kWh}{m^2}) \tag{4.12}$$

To evaluate a continuous investment choice of households, we estimate functions for investment costs, CO_2 emissions, and fuel prices based on real data (BAFA, 2021, Danish Energy Agency, 2021, Pickert et al., 2022). The heating technologies include oil and gas condensing boilers with and without solar thermal support and an air-source heat pump. As in the theoretical model, the functions are formulated concerning the heating technology's energy intensity level fph. We assume a system lifetime and an assessment period of 20 years. Table 4.1 shows the resulting technology functions.[29] It should be noted that fuel prices incorporate consumer taxes, including value-added tax, as well as electricity and gas taxes. Additionally, electricity prices include the costs of emission certificates derived from the European Emission Trading System. When interpreting the numerical results, one should keep in mind that these intricacies introduce distortions in optimal policy instruments and deadweight loss.[30]

Table 4.1.: Estimated continuous functions of investment costs, CO_2 emissions, and variable costs.

	Unit	Function	Data
Investment costs	€	$c(fph) = 14,100e^{-1.019 \cdot fph}$	Fitted function illustrated in the left plot in Figure C.2. Underlying fph data from column 3 and costs from columns 4 and 5 in Table C.2.
CO_2 emissions	kg/kWh	$epf(fph) = -0.110 + 0.358 \cdot fph$	Fitted function illustrated in the middle plot in Figure C.2. Underlying fph data from column 3 in Table C.2 and emissions derived from column 3 of Table C.3.
Fuel price	€ /kWh	$p(fph) = 0.394 - 0.331 \cdot fph$	Fitted function illustrated in the right plot in Figure C.2. Underlying fph data from column 3 in Table C.2 and prices derived from column 2 of Table C.3.

[29] Appendix C.3.3 presents the underlying data and the computation of the technology functions.

[30] One distortion, for example, is that since the electricity sector in Germany has not been fully decarbonized, electricity prices today do not reflect the price of zero-emission electricity. These could be higher, and the results would change accordingly.

4.3.2. Results

Continuous model

From the negative gradient of the fuel price in Table 4.1 follows that $p'(fph) < 0$. Considering Proposition 2 from Section 4.2, $p'(fph) < 0$ means that a CO_2 price (or a subsidy) has to at least offset the decrease of the heating system's variable fuel price induced by increasing fph. For such a CO_2 price, present bias leads to under-investment and, consequently, under-consumption of thermal energy. The numerical results replicate this finding on the relationship between present bias, investment, and consumption choices, as illustrated in Figure 4.2. In case of no present bias, $\beta = 1.0$, there is no investment up to a CO_2 price of 137€ /tCO_2. The chosen indoor temperature at this price is 17.8°C. With an increasing CO_2 price, the investments in lower fph increase. As heating costs decrease, the indoor temperature increases, which is commonly referred to as the rebound effect. At a CO_2 price of 192€ /tCO_2, the household invests in zero-emission heating technology and reaches the corresponding indoor temperature of 18.2°C. As described in Section 4.3.1, we interpret this carbon tax rate τ_t^{neu} as the implied emission damage to evaluate social welfare and consequently deadweight loss. In the presence of present bias, the household invests less and chooses a lower indoor temperature.

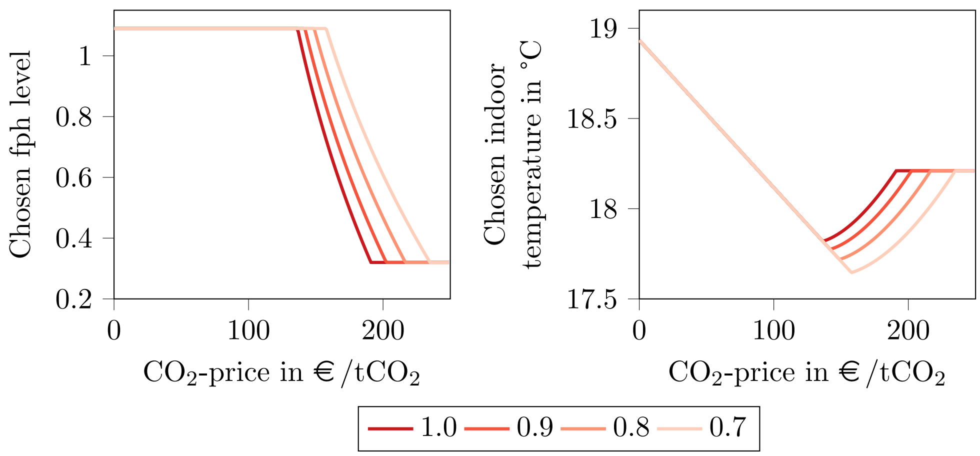

Figure 4.2.: The chosen fph and indoor temperature levels depending on the CO_2 price for present biases of 1.0, 0.9, 0.8, and 0.7.

Figure 4.3 shows that the total CO_2 emissions over the 20 years of heating system lifetime follow the household's investment and consumption choices. As discussed in Section 4.2.3, the investment in lower fph impacts emissions more than decreasing indoor temperature. In case of $\beta = 0.7$, emissions decrease from 81 tCO_2 to 75 tCO_2 for a CO_2 price increase from 0€ /tCO_2 to 157€ /tCO_2, due to the decrease in temperature. The emission decline turns more significant once the investments in lower fph start at 158€ /tCO_2. At an emission price of

235€ /tCO_2, the household invests in the zero-emission technology so that total CO_2 emissions are 0.

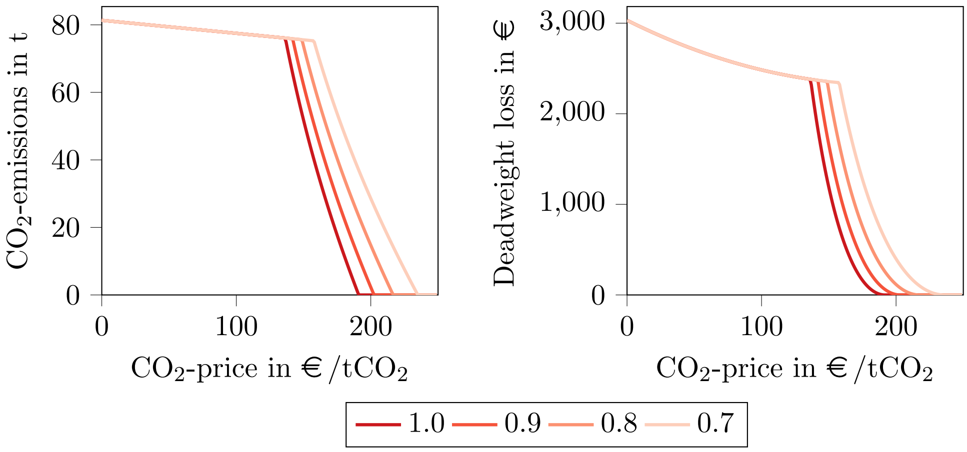

Figure 4.3.: Total emissions and deadweight loss over the heating system's lifetime of 20 years depending on the CO_2 price for present biases of 1.0, 0.9, 0.8, and 0.7.

The deadweight loss over the heating system's lifetime of 20 years is illustrated in Figure 4.3. It is based on the two-step procedure described in Section 4.3.1 and follows the chosen fph level. The deadweight loss constitutes the difference to the case of an investment in the zero-emission technology in investment costs, heating costs, gained utility from indoor temperature, and emission damage. Whereby the emission damage is calculated by applying the minimal target-consistent carbon tax rate inducing investments suitable for zero-emission goals. The resulting deadweight loss is mainly driven by the emission damage reduced by benefits through lower investment and heating costs. Without a CO_2 price, the household invests in the option with the highest fph, leading to a deadweight loss above 3,000€ due to the emissions. With an increasing CO_2 price, the indoor temperature first decreases slightly and with it, consequently, the emissions. Once the household invests in lower fph, the deadweight loss decreases convexly. Without present bias, the carbon tax rate τ_t^{neu} of 192€ /tCO_2 is sufficient to incentivize investment in the zero-emission technology. As Proposition 2 in Section 4.2.3 suggests, present bias leads to a deadweight loss caused by under-investment and, consequently, under-consumption. For $\beta = 0.9$, $\beta = 0.8$ and $\beta = 0.7$ the deadweight loss at τ_t^{neu} is 58€ , 252€ , and 613€ , respectively. The loss results from the present bias internality as the τ_t^{neu} addresses the emission externality. In Section 4.2.3, we argue that under a zero-emission target regime, a mark-up on top of the CO_2 price, which addresses the externality, can address the internality and reach the zero-emission technology. The required mark-ups in the case study for $\beta = 0.9$, $\beta = 0.8$ and $\beta = 0.7$ are 11€ /tCO_2, 25€ /tCO_2, and 43€ /tCO_2, respectively.

According to Proposition 3 in Section 4.2.3, a subsidy is an alternative to a mark-up on the carbon tax. If the subsidy is high enough to induce investments in heat pumps, no CO_2 price is needed since subsequent heating does not emit CO_2. Consequently, a negative relationship exists between the two policies. All policy combinations that lead to the social optimum are illustrated in Figure 4.4. The function's slope describing the relationship between policies depends on the level of present bias and is lower for a high present bias. The slope differences originate from the differing times at which subsidies and CO_2 prices affect the household. Present bias hinders households from fully considering the CO_2 price in their optimal choice problem. Subsidies take effect directly at the time of the investment. The higher the level of present bias, the more the CO_2 price must increase to reduce the required subsidy.

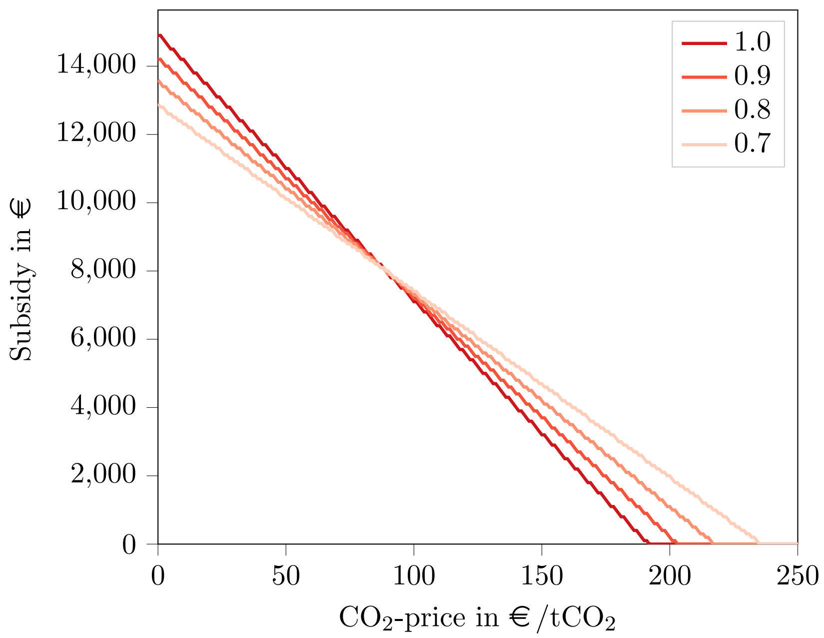

Figure 4.4.: Combinations of CO_2 price and subsidy that lead to the social optimum for present biases of 1.0, 0.9, 0.8, and 0.7.

At a CO_2 price of 89€ /t and a subsidy of 8,000€ , there is an intersection of the functions for the different levels of present biases. Thus, at this combination of CO_2 price and subsidy, the required policy for the social optimum is independent of the level of present bias. The policy combination's CO_2 price creates parity between the variable costs of all technology options. In other words, the variable costs become independent of the chosen fph. We identify this intersection in Proposition 2 in Section 4.2.3 by stating that present bias leads to under-investment and, consequently, under-consumption as long as total future discounted heating costs, including fuel and emission costs, for a marginal increase in fph are greater than or equal to zero. If this is not the case, i.e., less efficient heating systems have lower future heating costs, present bias will lead to over-investment. At the intersection between both cases, when future discounted heating costs are equal for all fph, the investment costs determine the investment choice. As present bias affects the household's weighting between marginal changes in investment costs and marginal changes in total future discounted costs, it does not affect the household's decision for equal future discounted costs. 89€ /t is the CO_2 price, which offsets the differences in the fuel costs. In this case, the subsidy must compensate households for the difference in investment costs between CO_2-emitting and zero-emission technologies. This subsidy is 8,000€ . As a result, the policy mix at the intersection of the functions is optimal, independent of the level of present bias.[31]

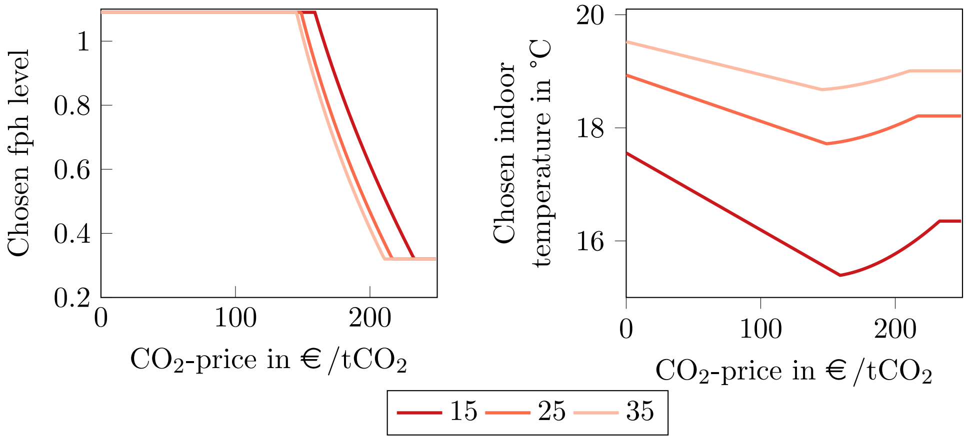

Figure 4.5.: The chosen fph and indoor temperature levels depending on the CO_2 price for valuation factors of 15€ /ΔT^2, 25€ /ΔT^2, and 35€ /ΔT^2.

The utility function of households is a critical assumption. As shown in Appendix C.3.1, we identify different valuation levels for indoor temperature. Figure 4.5 shows the fph level and chosen indoor temperature over CO_2 price for three different valuation factors given a present-bias of $\beta = 0.8$. A higher valuation factor implies a lower necessary CO_2 price to incentivize investments in fph. In the case of a low valuation factor, the household reacts first with decreasing indoor temperature, as this yields lower utility loss compared to the additional costs of investing, as is shown in the right part of Figure 4.5. As soon as investments in more efficient technologies are profitable, efficiency increases, and the household increases the indoor temperature until the installation of the zero-emission backstop technology.

The CO_2 emissions and deadweight losses over the heating system's lifetime of 20 years illustrated in Figure 4.6 show a slight decline until the start of investments in lower fph followed by a convex decline until the investment into the zero-emission technology. Before investments in more efficient technologies start, the deadweight loss is the highest for the high valuation factor since the under-consumption of indoor temperature weighs the most. The same logic also applies to why households with a high valuation factor start investing in more

[31] The values of the optimal policy mix depend on the assumptions fed into the model, like fuel prices, heating efficiencies, and the utility function.

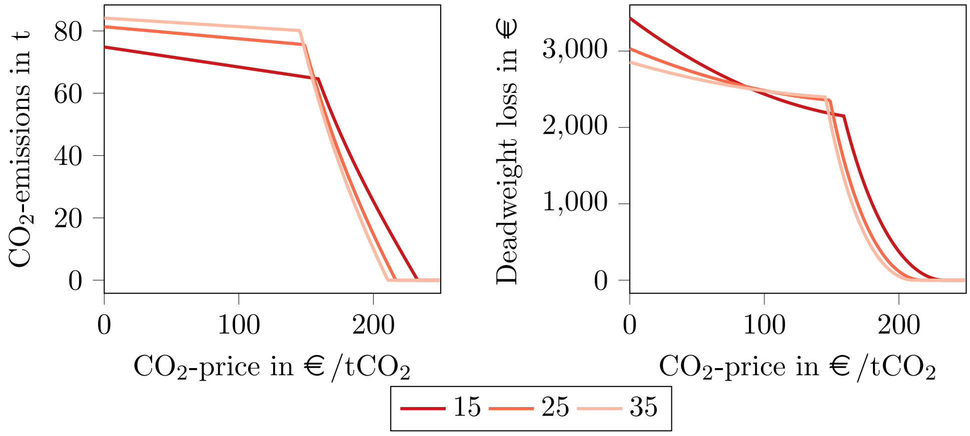

Figure 4.6.: Total emissions and the deadweight loss over the heating system's lifetime of 20 years depending on the CO_2 price for valuation factors of 15€ /ΔT^2, 25€ /ΔT^2, and 35€ /ΔT^2 and a present bias of 0.8.

efficient heating systems at lower CO_2 prices than households with lower valuation factors. As a higher level of investments decreases the deadweight loss not only through increased efficiency but also through reduced fuel costs, they exhibit a quadratic effect on the deadweight loss. Thus, the decline in welfare is less significant for lower valuation households, which still react by decreasing indoor temperature.

Discrete model

So far, the presented theoretical and numerical results assume continuous technology options so that all fph levels are feasible between the zero-emission and the least efficient option. In reality, there is only a limited set of heating technologies. Figure 4.7 illustrates the household's investment and consumption choices, given a discrete technology set, including an oil condensing boiler, a gas condensing boiler, both boilers combined with solar thermal, and an air-to-water heat pump. We define the set of technologies as the available fph levels from Section 4.3.1 and choose the cost and emission levels according to the functions from the continuous model (see Appendix C.3.3).

For each present bias level, there are four break-even CO_2 prices that lead to a technology switch. In case of no present bias, i.e., $\beta = 1.0$, the household invests in the highest fph of 1.09, i.e., the oil condensing boiler, until a CO_2 price of 139€ /tCO_2. For higher prices, the household chooses a fph of 1.02, i.e., the gas condensing boiler. The break-even points for investing in the oil condensing boiler combined with solar thermal and the gas condensing boiler combined with solar thermal are at 145€ /tCO_2 and 150€ /tCO_2 respectively. At a CO_2 price of 170€ /tCO_2, the household invests in the heat pump. Thus, in the discrete case 170€ /tCO_2 is the carbon tax rate τ_t^{neu} that induces investment

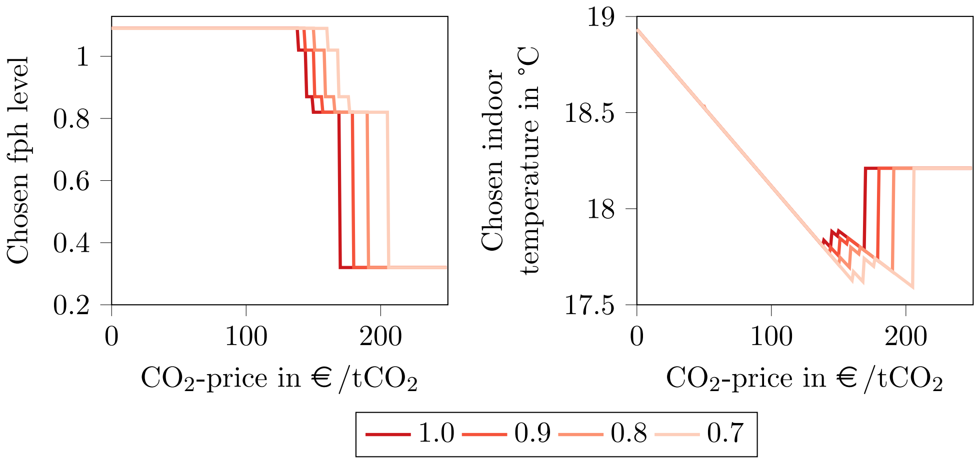

Figure 4.7.: The chosen fph and indoor temperature levels in case of discrete technology options depending on the CO_2 price for present biases of 1.0, 0.9, 0.8, and 0.7.

in the zero-emission technology. The τ_t^{neu} is lower in the discrete case than in the continuous case because the CO_2 price only has to create a break-even between the gas condensing boiler with solar thermal and the heat pump, and not between an infinitesimally less efficient heating technology and the zero-emission backstop technology. Analogously to the continuous case, present bias leads to under-investment and under-consumption.

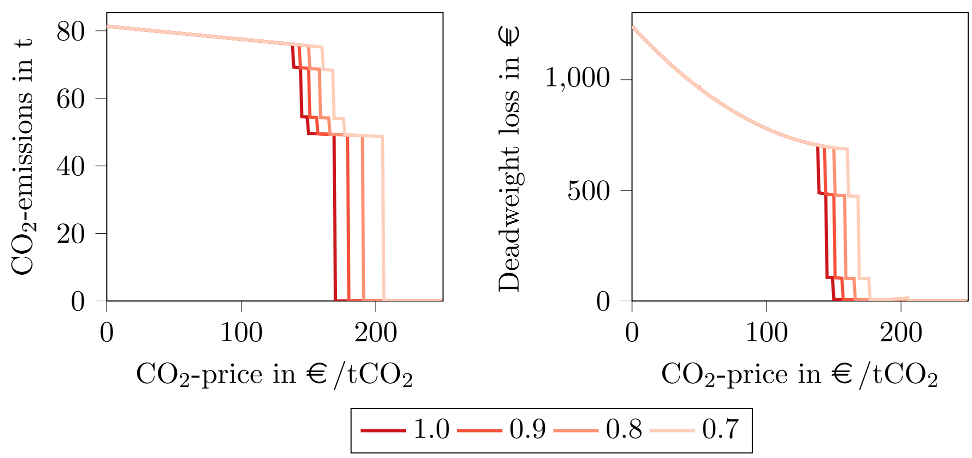

Figure 4.8.: The total emissions and deadweight loss over the heating system's lifetime of 20 years in the case of discrete technology options depending on the CO_2 price for present biases of 1.0, 0.9, 0.8, and 0.7.

The total CO_2 emissions over the heating system's lifetime of 20 years in Figure 4.8 mirror the step function of fph. There is a nearly linear decrease in CO_2 emissions following the household's temperature decreases and a more significant step whenever the CO_2 price causes a switch between two heating technologies. At the carbon tax rate τ_t^{neu}, there are zero CO_2 emissions in case of no present bias. The under-investment, due to present bias, leads to CO_2 emissions increases. These increases are for present biases of $\beta = 0.9$, $\beta = 0.8$, and $\beta = 0.7$, 49tCO_2, 49tCO_2, and 54tCO_2. This step is significantly higher than in the continuous case, as the next available technology is a gas condensing boiler with solar thermal compared to a technology with infinitesimally higher emission intensity. A mark-up on the CO_2 price can address the internality and incentivize investment in the heat pump, as stated in Section 4.2.3. For $\beta = 0.9$, $\beta = 0.8$, and $\beta = 0.7$, the mark-up is 10€ /tCO_2, 21€ /tCO_2, and 36€ /tCO_2, respectively. Following the two-step procedure described in Section 4.3.1, the implied damage from CO_2 emissions τ_t^{neu} is lower than in the continuous case, naturally resulting in a lower total level of deadweight loss. The deadweight loss due to present bias from under-investment and under-consumption is 101€ for a present bias of $\beta = 0.7$. The household chooses the oil condensing boiler with solar thermal instead of a heat pump. For present biases of $\beta = 0.9$ and $\beta = 0.8$ the household chooses a gas condensing boiler with solar thermal, which leads to negligible deadweight loss since τ_t^{neu} is defined as the necessarily implied damage to break-even between the two heating technologies.

4.4. Discussion

In our stylized model, we find that single-instrument policies can be welfare optimal and target-consistent even if the household is present biased. We implicitly assume that all households, their valuation factors, and their level of present bias are homogeneous. Accounting for household heterogeneity, however, implications of policy instruments can differ, especially in distributional effects.

According to our analysis, the lower the valuation for heat, the higher the CO_2 price must be to induce investment in the zero-emission backstop technology. Assuming the policymaker introduces a CO_2 price sufficient for incentivizing investment into the zero-emission backstop technology for a household with an average valuation factor, low-valuation households would not invest in the zero-emission technology. Instead, they would pay the CO_2 price and heat less, while high-valuation households invest in the zero-emission backstop technology. Similarly, if instead of a CO_2 price, the policymaker sets a target-consistent subsidy for average households, low-valuation households will not invest sufficiently. For households with higher valuations, however, the subsidy is not only sufficient but too high: they receive more money from the state than would have been necessary to stimulate the investment. The empirical literature suggests that high-income households have a higher valuation for thermal energy than low-income households (Cayla et al., 2011, Mertesacker, 2021). This would imply that a single, uniform subsidy, which aims to reach households with low valuation factors as well, favors high-income households.

Households also show heterogeneity regarding their level of present bias. Assume the policymaker sets a CO_2 price that is target-consistent for households with average present bias. As shown in Section 4.3.2, households with stronger present bias ($\beta < \bar{\beta}$) would underinvest and pay the CO_2 price in future periods, heating less than optimal. Literature estimations of the correlation between income and the present bias level range between no correlation and a negative correlation, suggesting that low-income households experience higher levels of present bias (Can and Erdem, 2013, Filippini et al., 2021, Meier and Sprenger, 2010).

Based on the above, it might therefore make sense for the policy maker to set a CO_2 price that is target-consistent for households with the highest present bias to have a target consistent CO_2 price for all households. However, there is another real-world issue that our stylized model does not consider. In reality, investment distortions exist, hindering households from investing. Possible distortions and, thus, obstacles to investment include budget constraints, lack of access to capital, technological or regional circumstances, or split incentives between landlords and tenants. In cases where households cannot invest, otherwise target-consistent CO_2 prices may lead to high costs. And these costs increase with the height of the chosen price. Subsidies can help to overcome budget constraints and lack of access to capital. Suppose a subsidy is introduced as a single instrument. In that case, there is no price signal to at least partially internalize the externalities of households that cannot invest and whose heating is still associated with GHG externalities.

According to the Tinbergen rule (Tinbergen, 1952), each political goal needs its own political measure. For instance, income effects of certain political interventions can be addressed more efficiently and more consistently by non-linear income taxation. Nonetheless, the distortionary effects and the investment barriers discussed above could partly be addressed by targeted subsidies or non-linear taxes on energy consumption. Targeted subsidies may incentivize certain households to invest in zero-emission heating technologies, either otherwise being unable to invest or having too low of a valuation for heat. Nonlinear taxation may alleviate burdens to lower income households, in the case that the CO_2 price does not lead to the investment into zero-emission technologies and heating still produces emissions. Both these options are difficult to implement and need robust empirical evidence, which we therefore do not further elaborate on.

We show in Section 4.3.2 that an optimal policy combination of a CO_2 price and subsidy exists that can account for different (unknown) levels of present bias.

The policy instruments also differ regardless of households' heterogeneity. In the case of a singular implementation of a CO_2 price or bans on GHG emitting technologies, the households bear the full costs. With (supplementary) subsidies, by contrast, the state pays (part of) the costs. The latter may make sense from a social justice perspective or to increase acceptance among the population.

Our assumption that there is a backstop technology at finite costs available may be oversimplified when considering real-world applications. Even within one sector, the costs of backstop technologies can vary between households and in time (Acemoglu et al., 2012). The differences might become even more pronounced when comparing across sectors, such as heating and aviation. Policy mechanisms must account for the fact that a uniform cross-sectoral CO_2 price could incentivize backstop technology adoption in one sector while leaving it uneconomical in another. For example, while a CO_2 price alone might suffice to drive adoption in one sector, another sector may require additional, targeted, technology-specific investment subsidies to achieve similar outcomes.

Furthermore, governments themselves could potentially be present biased, which could affect the effectiveness of measures to correct internalities. These aspects of government were excluded in this study, which assumed a social planner with a complete long-term orientation. However, elected officials are often under pressure to implement short-term solutions such as temporary tax cuts or spending increases before elections, complicating the design of policies for long-term welfare improvements. As mentioned in the literature review, one approach to addressing governments own potential present bias is to establish institutions like independent central banks, fiscal rules, or automatically adjusting spending for social security systems and other areas of government. Central banks, for example, often operate under rules designed to take a long-term view. While these rules are not infallible and may sometimes be broken, they provide a framework that can help mitigate the short-term political pressures prevalent in political decision-making.

Given the heterogeneity of households and their potential investment constraints, as well as the possible desirability of distributing costs between households and the state, there are arguments in favor of combining taxes (or bans) with subsidies. By distinguishing the effects of policies on investment and utilization decisions, our analysis can support a nuanced discussion of appropriate policy mixes.

4.5. Conclusion

The present chapter examines the impact of present bias on optimal environmental policies aimed at achieving zero emissions. The study generalizes Heutel's model for policy design for externality-producing durable goods when internalities are present. Besides increasing efficiency, investments in a new heating system may substitute the fuel used. Accounting for this substitution adds the dimensions of fuel price and emission intensity to our technology space. The generalization allows us to include a backstop technology with finite cost and analyze policy choices that reach zero emissions.

This work contributes to the scientific literature in three ways. First, we generalize Heutel's model by allowing technologies to differ in fuel price and emission intensity. Second, we introduce a model framework for developing target-consistent environmental policies given a backstop technology. It can serve as one element within a toolbox for welfare analysis given political targets beyond externality pricing. Third, we apply the model framework to the case of decarbonization in the German heating sector of private households under present bias and derive numerical magnitudes of the present bias effects.

We find that, generalizing Heutel's propositions, one instrument can be sufficient to address both externality and internality. Still, a combination of subsidies and taxes can be advantageous, as we show that there exists a tax-subsidy combination that is optimal regardless of the present bias level. This finding can be applied to comparable investment decisions in externality (GHG emission) producing durable goods, such as private mobility investments. The existence of the optimal policy mix is particularly relevant because the level of present bias is private information unknown to the policymaker and heterogeneous among households. Policymakers could avoid distributional effects by utilizing the present bias agnostic optimal policy mix. There are further arguments supporting policy mixes that fall short in our stylized model, including heterogeneity in the valuation of heating, investment distortions, and the costs' distribution between households and the state.

Based on our analysis, there remains room for further research. In contrast to our greenfield analysis with constant prices, in reality, households already own heating systems, and the heating system stock's age structure is heterogeneous. Therefore, households are faced not only with the question of which technology to invest in, but also whether it is worth investing in a new heating system early on before the existing one breaks down. This raises questions about the timing of policy instruments, e.g., concerning the interdependencies of price paths of CO_2 taxes or fuel prices over time. Here, as well, the question arises as to what constitutes target-consistent policy instruments. The issue could prove complicated, as it is difficult to determine under which circumstances early heating systems replacement is required to achieve climate targets. Further, we discussed the role of household heterogeneity in our findings qualitatively. Households differ in their level of present bias, their current heating systems, and their financial capabilities. A more detailed examination of these properties could, in addition to theoretical analyses, e.g., concerning optimal policy mixes across households, also quantify effects at the level of the entire German building stock.

5. Digitalization and energy consumption in the EU: sector-specific impacts and mediating factors

5.1. Introduction

The digital transformation and energy transition are reshaping modern economies. Information and communication technology (ICT) has become a key driver, with global digital transformation spending projected to reach $3.9 trillion by 2027, growing at 16.1% annually (IDC, The International Data Corporation, 2024). Meanwhile, the International Energy Agency's *Net Zero Emission by 2050* scenario assumes a 14% decline in per capita energy consumption by 2030 (IEA, 2023b). The two shifts raise a central question: *How does the growth of the digital economy, powered by ICT capital, affect energy consumption?*

Examining the interaction between digitalization and energy consumption requires clear definitions of both. Technically, digitalization refers to the "increased computation, storage, and transmission of data" (Goldfarb and Tucker, 2019). Generalizing the concept, Lange et al. (2020) describe digitalization as "the increasing application of ICT throughout the economy and society". In this paper, digitalization is defined as the share of ICT capital —including computation, communication, and software or database assets— in total capital. Energy consumption refers to the use of final energy to deliver services, such as heat, lighting, or mechanical force. According to Hunt and Ryan (2015), energy consumption depends total disposable income for consumption, the menu of energy services offered, and the efficiency state of the technologies providing the services.

Reflecting on this definition, the specific impact of digitalization can be expected to vary across energy services, which are commonly categorized into sectors such as industry, transport, and residential (Enerdata, 2023a). The increasing shares in ICT capital may affect the share of industrial processes in the total economy, resulting in a restructuring of the economy (World Bank, 2023a). In the transport sector, digitalization may improve route choices and optimize vehicle utilization, thereby increasing the sector's energy efficiency (European Commission, 2020, Noussan and Tagliapietra, 2020, Turan et al., 2023). Lastly, the residential sector offers a distinctive perspective on how digitalization alters domestic energy consumption (Paneru and Tarigan, 2023). Smart technologies, such as smart meters and home automation systems, enhance energy efficiency by allowing better control and monitoring of energy use in households. The sector-specific effects illustrate the complexity and diversity of digitalization's impact on disaggregated energy consumption.

The European Union (EU) offers a compelling case for examining the relationship between digitalization and energy consumption, combining advanced digital infrastructure, ambitious climate policies, and diverse energy systems among its 27 member states (former 28). The EU's commitment to becoming carbon-neutral by 2050, set out in the European Green Deal, highlights the need to understand how digital transformation impacts energy demand and usage patterns across sectors (Fetting, 2020). The Digital Decade Policy Program (DDPP), launched in January 2023, reflects the EU's integrated approach to digitalization and environmental objectives. By promoting investments in smart technologies and advanced connectivity, the DDPP aims to enhance real-time energy monitoring and efficiency—both crucial to meeting the EU's climate goals (European Commission, 2023).

Against this backdrop, this paper investigates the question: *How does the relative importance of ICT capital in the economy influence sector-specific energy consumption patterns in the EU, and through which key mediating factors does this influence occur?* The question is particularly relevant given the recent surge in digital technology adoption. To our knowledge, this is the first study to specifically address it at the sectoral level. We examine the relationship between digitalization, proxied by the share of ICT capital, and energy consumption in the EU's industrial, transport, and residential sectors.

We contribute to the literature in three ways. First, we investigate the effect of digitalization on energy and electricity consumption in the EU from 2007 to 2020. The examination sheds light on key aspects of the energy transition, specifically the reduction of final energy consumption and the electrification of energy use. To capture dynamic effects, we employ the system generalized method of moments (system GMM). Second, we extend our analysis to the sectoral level, examining how digitalization affects energy consumption in the industry, transport, and residential sectors. The approach reveals heterogeneous impacts across economic domains. Third, we explore mediating factors that influence the relationship between digitalization and energy consumption, focusing on structural and efficiency effects. Sector-specific energy efficiency indicators are used to quantify efficiency changes.

Our results can be summarized as follows. First, energy and electricity consumption in the EU-28 exhibit strong persistence, with past usage levels closely predicting current consumption. Second, digitalization, measured by the share of ICT capital, is associated with reductions in both overall energy and electricity consumption, suggesting efficiency gains and potential shifts towards less energy-intensive economic structures. Specifically, a 10% increase in the ICT capital share correlates with approximately a 0.74% decrease in energy consumption and a 0.47% decrease in electricity consumption. Third, sectoral analysis shows consumption reductions in the industry and residential sectors, while the transport sector shows no significant effect, highlighting sector-specific dynamics. Lastly, our exploration of the indirect effects of digitalization reveals that, in the industry sector, the impact is mediated by shifts towards less complex, and potentially less energy-intensive, activities and improvements in energy efficiency. In the residential sector, the positive role of digitalization in enhancing energy efficiency is evident, underlining the importance of smart and efficient technologies in reducing consumption.

The remainder of this chapter is structured as follows. Section 5.2 provides a conceptual background on the relationship between digitalization and energy consumption. Section 5.3 describes the empirical approach. In Section 5.4, the data used is presented. Section 5.5 shows empirical findings, and Section 5.6 discusses their implications. Finally, Section 5.7 concludes.

5.2. The relationship between digitalization and energy consumption

Exploring factors influencing energy consumption is an established area of scholarly inquiry. Recently, including digitalization as a potential determinant has added a new dimension to the field. Thus, the literature on energy consumption determinants can be categorized into three strands: identifying the principal factors that drive energy consumption, integrating digitalization within these factors, and developing approaches to measure digitalization.

An extensive body of literature focuses on the determinants of energy consumption, primarily examining the impacts of economic activity and energy prices (e.g., Ahmad et al., 2020, Kraft and Kraft, 1978, Ozturk, 2010). These studies consistently find that energy consumption positively correlates with income and negatively with energy prices. Moreover, recent studies have expanded the traditional energy consumption function by incorporating additional factors. Both theoretical and empirical research have begun to explore the influence of industrial structure, financial development, R&D expenditures, and demographic trends on energy consumption (Adom et al., 2012, Lee et al., 2021, Mi et al., 2015), financial development (Acheampong, 2019, Sadorsky, 2010), research and development expenditures (R&D) (Churchill et al., 2021, Godil et al., 2021), and demographic structure (Liddle, 2014) as potential drivers of energy consumption. The studies commonly find that an economy's industrial structure often correlates with its energy consumption, with more industrialized economies generally consuming more energy. Other factors, such as financial development, indirectly shape energy consumption via economic and technological shifts.

As the role of digitalization in the global economy intensifies, a growing body of research has started to explore its effects on energy consumption, reporting seemingly conflicting results regarding the effects' direction. Some studies, such as Schulte et al. (2016) and Han et al. (2016), find that increasing digitalization correlates with lower energy consumption. In contrast, others, including Kouton (2019), Saidi et al. (2017), and Sadorsky (2012), argue that the effects of digitalization are associated with an increase in energy consumption. The conflicting results partially stem from the use of different econometric approaches and the analysis of different samples of countries and periods, which likely reflect various growth phases of digitalization. Additionally, many of the studies do not consider the mediating factors through which digitalization affects energy consumption.

To clarify the mediating factors in the relationship between digitalization and energy consumption, Lange et al. (2020) employ an analytical model that pinpoints key energy consumption reducing channels such as structural changes and energy efficiency. In their analysis, they provide a real-world interpretation of the factors. Digitalization is seen as a driver of structural change in an economy, often leading to a greater emphasis on the tertiary (services) sector, as digitalization typically enhances the provision and efficiency of service-oriented activities. Regarding energy efficiency, digitalization promotes advancements through dematerialization—reducing the material and energy intensity of processes—and optimizing production processes to enhance energy use efficiency. The empirical significance of these channels has been considered in the literature (e.g., Börjesson Rivera et al., 2014, Koomey et al., 2013, Lange et al., 2020). However, the review by Horner et al. (2016) illustrates that the observed results depend highly on the specific scope and variables defined by researchers. Consequently, studies focusing on the total effect of digitalization on energy consumption (Schulte et al., 2016), the direct effect (Aebischer and Hilty, 2015, Andrae, 2019) or only one indirect effect, e.g., sectoral change (Fix, 2019, Rieger, 2020) or energy efficiency (Joyce et al., 2019, Santarius et al., 2020), are hardly comparable.

Recognizing the gaps in the literature, few studies have attempted to unify the seemingly conflicting results within a comprehensive empirical framework. Recently, Xu et al. (2022) and Ren et al. (2021) have conducted mediation analyses to understand the interplay between digitalization and energy consumption, recognizing both direct and indirect effects. While Ren et al. (2021) focus on China, Xu et al. (2022) examine a sample of 109 major economies worldwide. Collectively, the studies apply seven variables that relate to the mediating factors identified by Lange et al. (2020): (1) factors like industrial structure distortion and upgrading pertaining to changes in economic structure; and (2) elements including human capital, financial development, and technological innovation and progress, which are associated with the technical channel (i.e., energy efficiency). Although the measures effectively convey digitalization's impact through general economic dimensions, they do not offer a clear energy interpretation akin to that provided by Lange et al. (2020). Our research aims to develop measures for mediating factors in alignment with Lange et al. (2020). It considers the diversity of energy services across various sectors and relates them closely to an energy-centric interpretation, utilizing reproducible European data.

Given the varied impacts of digitalization identified in prior research, understanding the definitions and measurements of digitalization is essential. Accurately defining measures of digitalization presents a significant challenge (Coyle and Nguyen, 2019, Goodridge et al., 2021), as reflected in the energy consumption literature, which employs a range of measures to analyze the effects of digitalization on energy use. The measures encompass *access and usage metrics*, focusing on the extent of digital technology's penetration within a society, such as the percentage of internet users and mobile cellular subscriptions (e.g., Kouton, 2019, Sadorsky, 2012, Usman et al., 2021); *composite indices*, aiming to capture both the breadth and depth of digital penetration by combining multiple indicators to provide a more comprehensive overview of digital penetration and its sophistication within an economy (Lin and Huang, 2023, Shahbaz et al., 2022, Xu et al., 2022); and *economic investment metrics*, reflecting the intensity of commitment to digital transformation from an economic investment perspective, such as ICT capital (e.g., Bernstein and Madlener, 2010, Hanclova et al., 2015, Xu and Zhong, 2022).

From the literature reviewed above, three main findings emerge. First, although most studies examine the effects of digitalization on aggregated energy consumption, understanding of its impact on specific sectors or consumption areas remains limited. The research gap underscores the need for more detailed investigations into the varied influences of digitalization across energy use sectors. Second, in their aim to establish a comprehensive empirical framework, many studies rely on general economic measures, such as human capital and financial development, as proxies for the indirect effects of digitalization. The approach that empirical analysis fails to integrate measures informed by energy economics for the indirect effects when examining the relationship between digitalization and energy consumption. Lastly, empirical evidence focusing on the impact of digitalization on energy consumption within the European Union (EU) is limited, highlighting an opportunity for region-specific studies that could inform EU-centric policies and strategies.

Addressing the gaps, this paper extends the existing literature by analyzing the impact of digitalization on energy and electricity consumption at the sectoral level, specifically focusing on the industry, transport, and residential sectors. Our study explores the mediating roles of economic structure and energy efficiency in the digitalization-energy consumption relationship. Finally, our research provides nuanced insights into the EU specific dynamics. Our approach utilizes a unique EU-specific dataset to quantify digitalization as the share of ICT capital in total capital, including detailed, sector-specific ICT capital data for the industry, transport, and residential sectors.

5.3. Methodology

This section outlines the empirical strategy to assess the impact of digitalization on energy consumption, detailing the econometric framework and methods for addressing endogeneity.

5.3.1. Empirical strategy

We are particularly interested in understanding the effects of digitalization on both aggregate and disaggregate energy consumption, while identifying the relationship's mediating factors. Our hypothesis posits that a higher level of digitalization correlates with reduced energy and electricity consumption. We suggest that the negative effect is indirectly mediated by factors such as changes in economic structure and improvements in energy efficiency, in line with the findings of Lange et al. (2020).

Figure D.1 summarizes the three aspects of our empirical analysis. (1) The aggregate analysis illustrates the overarching correlation between enhanced ICT capital and energy usage. (2) A disaggregated analysis distinguishes among the industry, transport, and residential sectors. The sector specific examination reveals the nuanced dynamics of digitalization's impact on energy consumption. In the industry sector, digitalization fosters a shift towards service-oriented, less energy-intensive activities and enhances energy efficiency through improved control and optimization of manufacturing processes (Crozet and Milet, 2017, OECD, 2020, Paschou et al., 2020). For the transport and residential sectors, the emphasis lies on the advancement in energy efficiency facilitated by digital technologies such as smart systems in vehicles and homes that optimize energy use (Giannopoulos, 2004, Helmke, 2022, Lyons et al., 2019, Morán et al., 2016). (3) The mediation analysis refines the insights by exploring underlying mechanisms, such as the structural shift in the industry sector towards services and the overall enhancement of energy efficiency enabled by digitalization across sectors.

For the aggregated analysis, we calculate the overall share of ICT capital by summing the ICT capital across the industry, transport, and residential sectors and then dividing the total by the sum of capital across sectors. The aggregate ICT capital share is linked to energy and electricity consumption throughout the entire economy, establishing a base model for our study. In contrast, the disaggregated analysis focuses on the specific impacts within the industry, transport, and residential sectors. Here, we calculate the share of ICT capital to total capital within each sector, tailoring both the measures of digitalization and energy consumption to the corresponding sector. The approach allows us to illuminate the underlying effects identified in the aggregated analysis and to explore the observed effects and potential sector-specific mediating factors at a more granular level.

Two potential mediating variables could influence the relationship between digitalization and energy consumption. The first, related to the structure of the economy, focuses particularly on the industry sector. Lange et al. (2020) argue that digitalization may drive the economy toward tertiarization, facilitated by digital technologies that notably support the development of new service-oriented products. Consequently, we examine how a structural shift within the industry sector mediates the relationship between digitalization and energy consumption. The second potential factor linking digitalization to energy consump-

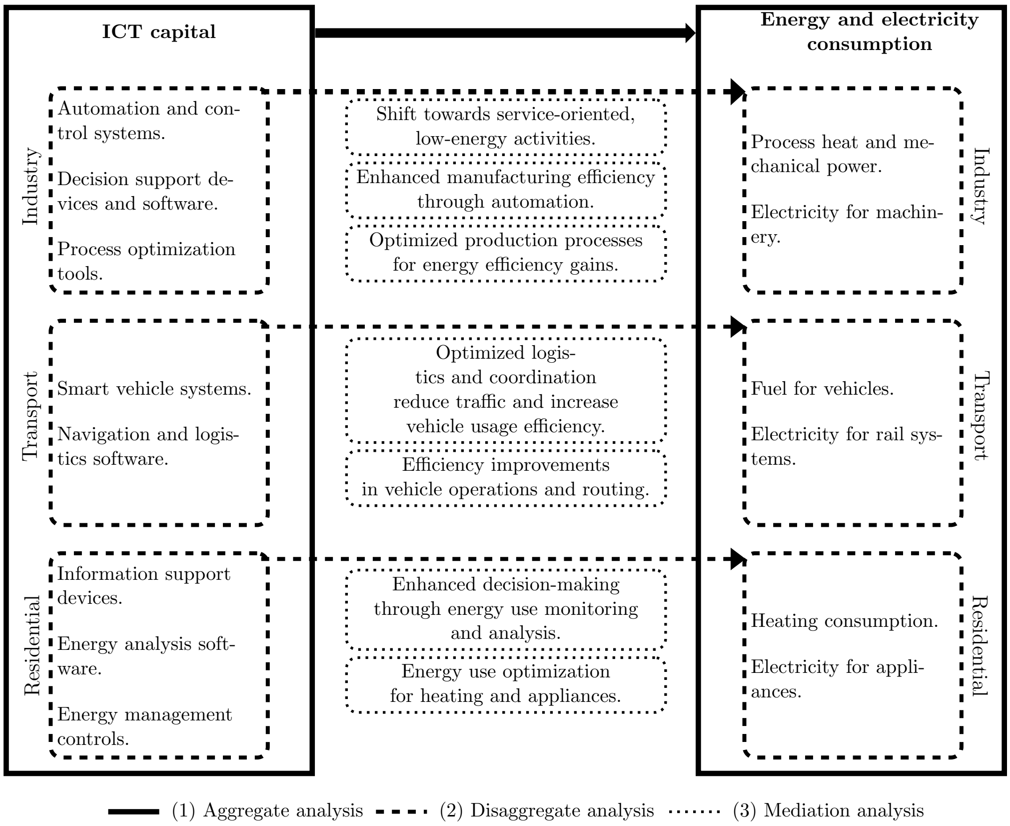

Figure 5.1.: Structure of the empirical approach including (1) aggregated, (2) disaggregated, and (3) mediation analysis of the relationship between ICT and energy and electricity consumption.

tion is the enhancement of energy efficiency in delivering energy services across the industrial, transport, and residential sectors. In the industrial sector, digital technologies can increase efficiency through improved technical control and automation of the machinery or optimized process controls (Lin and Huang, 2023). In the transport sector, beyond technological advancements within the vehicles, efficiency gains also stem from facilitated information and guidances of users, improved operation of networks, and freight transport systems (Giannopoulos, 2004). Meanwhile, in the residential sector, digitalization facilitates more efficient energy use through additional sensors and control systems, such as in smart thermostats (Lyons et al., 2019, Morán et al., 2016).

5.3.2. Energy consumption determinants and digitalization's impact

As highlighted in Section 5.2, the primary determinants of energy consumption in an economy are income and energy prices. Building on this understanding, our energy consumption model is based on this fundamental relationship, as shown in the following equation[32]:

$$ln(Energy\ consumption) = \beta_0 + \beta_1 ln(Income) + \beta_2 ln(Energy\ price) + \epsilon. \quad (5.1)$$

where income and energy prices are treated as endogenous variables, acknowledging that the factors not only influence energy consumption but are also impacted by it, forming a dynamic and interdependent relationship. The energy consumption function is further extended to include other covariates known to impact energy consumption: Heating degree days (HDD) serve as a proxy for variations in heating demand due to weather conditions, a dummy variable captures the effects of the financial crisis in 2009, and another dummy variable accounts for the COVID-19 pandemic in 2020. The variables are assumed to be exogenous to energy consumption. Thus, equation (5.1) is expanded as follows:

$$\begin{aligned} ln(Energy\ consumption) = {} & \beta_0 + \beta_1 ln(Income) + \beta_2 ln(Energy\ price) \\ & + \beta_3 ln(HDD) + \beta_4 ln(Fin.\ crisis) \\ & + \beta_5 ln(COVID) + \epsilon. \end{aligned} \quad (5.2)$$

Given our focus on the impact of digitalization on energy consumption, we incorporate digitalization as a key explanatory variable in the model, following the approach of Ren et al. (2021), Lange et al. (2020), and Schulte et al. (2016). Consequently, equation (5.2) is extended to include digitalization, resulting in the following formulation:

$$\begin{aligned} ln(Energy\ consumption) = {} & \beta_0 + \beta_1 ln(Income) + \beta_2 ln(Energy\ price) \\ & + \beta_3 ln(HDD) + \beta_4 ln(Fin.\ crisis) \\ & + \beta_5 ln(COVID) \\ & + \beta_6 Digitalization + \epsilon. \end{aligned} \quad (5.3)$$

In equation (5.3), income, energy prices, and digitalization are treated as endogenous variables. The factors not only influence energy consumption but are also impacted by it, forming a dynamic and interdependent relationship. We apply the model to both energy and electricity consumption. For the empirical analysis, equation (5.3) is re-parameterized into an estimable form as follows:

[32] The formal derivation of equation (5.1) aligns with the theoretical framework explained by Hunt and Ryan (2015).

$$
\begin{aligned}
ln(Energy\ consumption)_{it} = \beta_0 &+ \beta_1 ln(Income_{it}) \\
&+ \beta_2 ln(Energy\ price_{it}) \\
&+ \beta_3 Digitalization_{it} + \beta_4 ln(HDD_{it}) \\
&+ \beta_5 Fin.\ crisis_{it} + \beta_6 COVID_{it} + \epsilon_{it},
\end{aligned} \tag{5.4}
$$

where i refers to the country and t refers to the time period. Moreover, following the existing empirical literature (e.g., Çoban and Topcu, 2013, Sadorsky, 2010), energy consumption in the previous period has a dynamic effect on current energy consumption. Therefore, equation (5.4) is extended by the lagged dependent variable to equation (5.5), representing the model to be estimated to derive the effect of digitalization on energy consumption.

$$
\begin{aligned}
ln(Energy\ consumption)_{it} = \beta_0 &+ \theta_0 ln(Energy\ consumption)_{it-1} \\
&+ \beta_1 ln(Income_{it}) \\
&+ \beta_2 ln(Energy\ price_{it}) \\
&+ \beta_3 Digitalization_{it} + \beta_4 ln(HDD_{it}) \\
&+ \beta_5 Fin.\ crisis_{it} + \beta_6 COVID_{it} + \epsilon_{it}.
\end{aligned} \tag{5.5}
$$

5.3.3. Estimating indirect effects of digitalization on energy consumption

Our econometric approach to estimating the indirect effects of digitalization on energy consumption involves a three-step process, as outlined by VanderWeele (2016), Zhao et al. (2010), and Baron and Kenny (1986). Initially, the first step focuses on estimating the potential influence of digitalization on the mediating variables. Subsequently, the second step examines the impact of the mediating variables on energy consumption. In the third step, we apply the product method to compute the indirect effects.

In the first step, we estimate the effect of digitalization on each individual mediating variable within all mediating variables, resulting in one equation per mediating variable as depicted in equation (5.6). The set of $Covariates_{it}$ in each equation is tailored to the corresponding mediating variable. The coefficients α_2 in these equations capture the effects of digitalization on each mediating variable.

$$
\begin{aligned}
Mediating\ variable_{it} = \alpha_0 &+ \alpha_1 Mediating\ variable_{it-1} \\
&+ \alpha_2 Digitalization_{it} + \alpha_3 Covariates_{it} + \epsilon_{it},
\end{aligned} \tag{5.6}
$$

Following the notation in equation (5.5), the effect of the mediating factors on energy consumption can be estimated in the second step through equation (5.7). Here, we include all *Mediating variables* of the corresponding sector in the same energy consumption equation. In contrast to estimating one function per mediator, the approach accounts for potential effects between the mediating variables (VanderWeele, 2015). The formulation prevents us from counting mediating effects double, which might happen if they are estimated separately. The vector θ_1 contains the coefficients of the mediating variables in explaining the dependent variable energy consumption. If the equation accounts for all mediating effects, coefficient λ_3 would be the direct effect of digitalization on energy consumption.

$$\begin{aligned} ln(Energy\ consumption)_{it} = {} & \lambda_0 + \theta_0 ln(Energy\ consumption)_{it-1} \\ & + \theta_1 ln(Mediating\ variables)_{it} \\ & + \lambda_1 ln(Income_{it}) + \lambda_2 ln(Energy\ price_{it}) \\ & + \lambda_3 Digitalization_{it} + \lambda_4 ln(HDD_{it}) \\ & + \lambda_5 Fin.\ crisis_{it} + \lambda_6 COVID_{it} + \epsilon_{it}. \end{aligned} \tag{5.7}$$

Using the product method, the indirect effect of digitalization on energy consumption is calculated as the product $\theta_1\alpha_2$ (VanderWeele, 2016). A mediating effect is deemed significant if both coefficients θ_1 and α_2 are significant. The total effect is the sum of direct and indirect effects, represented as $(\lambda_3 + \theta_1\alpha_2)$. [33]

5.3.4. Addressing endogeneity in energy consumption modeling with GMM estimators

When estimating equation (5.5), we encounter a scenario where the lagged dependent variable serves as one of the explanatory variables, while simultaneously, the dependent variable might negatively influence the explanatory variable. This setup inherently introduces simultaneous endogeneity into the model. Therefore, we employ the system GMM estimator, as proposed by Arellano and Bover (1995) and further developed by Blundell and Bond (1998), to address the challenges of dynamic panel bias and the potential endogeneity of regressors. The choice of system GMM over traditional panel data estimation techniques such as Ordinary Least Squares (OLS) or the Within Group estimations is motivated by their inability to adequately control for these issues. Specifically, OLS estimates are biased and inconsistent due to the omission of unobserved time-invariant

[33] Note that we proceed with the mediation analysis even if digitalization demonstrates a statistically insignificant effect on energy consumption, as estimated in equation (5.5). The approach aligns with views expressed in the relevant literature, such as (Jiang et al., 2021, e.g.,), which argue that a significant effect is not essential for examining mediation effects.

country effects. The OLS levels estimate of the coefficient on the lagged dependent variable tends to be biased upwards, as it is positively correlated with the permanent effects in dynamic panel regressions. On the other hand, Within Group estimations attempt to mitigate this issue by controlling for unobserved country-specific effects. However, the estimate of the coefficient on the lagged dependent variable tends to be biased downwards (Hsiao, 2022, Nickell, 1981).

The system GMM estimator is designed to yield consistent and efficient parameter estimates in scenarios where independent variables are not strictly exogenous, as they are correlated with past and current error terms, and in cases characterized by heteroscedasticity and autocorrelation within individuals Roodman (2009). It effectively addresses endogeneity by instrumenting the lagged dependent variable and/or any other endogenous variables with instruments presumed to be uncorrelated with the fixed effects (Nickell, 1981, Roodman, 2009). The system GMM offers enhanced efficiency over the difference GMM estimator by assuming the first differences of instruments are not correlated with fixed effects, thus allowing the inclusion of more instruments. It also addresses the potential for downward bias in estimates due to weak instruments, a concern highlighted by (Roodman, 2009), and proves particularly beneficial for series resembling random walks, where difference GMM may introduce large finite sample biases Blundell and Bond (1998). Nevertheless, the system GMM is subject to a primary concern, which is the over-identification problem due to an excessive number of instruments. To avoid this issue, we limit our instruments by collapsing the instrument matrix and choosing fewer lags instead of exploiting all available lags as instruments (Bazzi and Clemens, 2013).

We conduct two key diagnostic tests to ensure the reliability of our GMM estimates. Firstly, we use the Arellano and Bond (1991) test to examine the residuals in differences, working under the null hypothesis that there is no serial correlation. Secondly, given that the system GMM estimator relies on instrumental variables, we implement the Hansen (1982) test for over-identifying restrictions, where the validity of the instruments constitutes the null hypothesis. It is generally acknowledged that two-step system GMM estimation yields more efficient estimates compared to one-step system GMM. However, it is important to note that the efficiency gain from using the two-step approach is relatively modest. Moreover, asymptotic standard errors associated with two-step GMM estimators can exhibit significant downward bias in small sample sizes (Blundell and Bond, 1998, Hoeffler, 2002). Given the limited number of groups in our analysis, we apply the one-step system GMM estimation method.

5.4. Data

Our empirical analysis employs panel data spanning from 2007 to 2020 for 28 EU countries, covering aspects such as energy consumption, digitalization, economic activity, economic structure, and energy efficiency. Table D.1 in Appendix D.1

comprehensively lists the variables used in our analysis. It provides summary statistics for each variable, including mean, minimum, maximum, and standard deviation values. Additionally, the table details the units of measurement for variables and distinct symbols assigned to them, which will be consistently used throughout the remainder of this paper. In the following, we outline the rationale behind selecting variables for our regression analysis, focusing on factors affecting energy and electricity consumption within the EU.

5.4.1. Main variables

The primary dependent variable is energy consumption, including both final energy consumption per capita and electricity consumption per capita, with a focus on the industry, transport, and residential sectors. Collectively, the sectors account for over 80% of the EU's final energy consumption, according to (Enerdata, 2023a). Our sector-specific approach significantly enhances the precision and relevance of our analysis, aimed at discerning the impact of digitalization on energy dynamics. By excluding non-energy uses, we ensure a more accurate evaluation of energy consumption patterns, thereby eliminating potential biases arising from activities unrelated to direct energy use.

Data on both aggregate and sector-specific energy and electricity consumption are derived from the IEA's World Energy Balances (IEA, 2023a). To facilitate a standardized comparison, we normalize the energy data by dividing the total energy consumption by the population size of each respective country, resulting in per capita energy consumption metrics. The population data necessary for the calculation are sourced from the World Development Indicators (World Bank, 2023b). The normalization technique is critical for adjusting for population size variations among the EU-28 countries, thereby ensuring that our analysis of energy consumption trends and patterns is meaningful.

Moving to the independent variables, digitalization represents our primary variable of interest. We utilize the January 2023 release of the EU-KLEMS Growth and Productivity Accounts to measure digitalization, which provides detailed data on investments in ICT (Information and Communication Technology) and non-ICT assets (Stehrer and Sabouniha, 2023). This dataset segments capital investments into three ICT categories—computing equipment, communication devices, and software—and non-ICT categories such as buildings, transport equipment, and other machinery. The data classification follows the NACE Rev. 2 1-digit system[34]. For our sector-specific analysis, we focus on the classes of *C Total manufacturing* (industrial sector), *H Transportation and storage* (transport sector), and *L Real estate activities* (residential sector). For consistency, we rely on the real estate sector as approximation of digitalization in the residential sector. In Appendix D.3, the disaggregate analysis is repeated with a

[34]The NACE Rev. is a statistical classification of economic activities in the European Community. For more information, refer to eurostat (2008).

consumption-side measure of digitalization. We derive sector-specific digitalization measures by calculating the ratio of total ICT capital to total capital stock for each sector, facilitating an assessment of digitalization's extent within them. An aggregated digitalization measure across the three sectors is computed based on the share of ICT capital.

Our analysis includes economic activity as the second independent variable due to its well-established correlation with energy consumption. We utilize Gross Domestic Product (GDP) as the primary metric to represent economic activity in the aggregated examination acknowledging its effectiveness in explaining scale differences in energy consumption. Across sectors, we keep GDP as a proxy for activity level, while we recognize that it may not fully capture structural differences. For instance, GDP alone may mask significant structural differences between countries in the industry, where variations in the composition of production can influence energy use. The structural aspects are addressed separately in the mediation analysis. For both the industry and the transport sector, GDP has been similarly applied as a proxy for activity in previous research (Ecola and Wachs, 2012, Salim et al., 2014). In the residential sector, we use private consumption (total household expenditure) as a proxy to more accurately capture the nuances of domestic activity levels and their impact on energy consumption. The choice is informed by the documented connection between household lifestyle, economic status, and energy use in Thomas and Rosenow (2020). Crucially, all economic indicators are expressed in real, per capita terms. The normalization is essential to ensure data are comparable across countries and time, mitigating spurious correlations arising from inflation and population growth.

We examine the impact of energy prices, recognizing their significant influence on the energy consumption behaviors of both consumers and industries. Higher energy prices generally lead to decreased consumption due to escalated costs, while lower prices may incentivize increased usage. We utilize the real energy price index for both industry and households, which incorporates levies and taxes, as provided by the IEA's Energy Prices and Taxes database (IEA, 2022). The index represents a quantity-weighted average of various energy products—such as oil, natural gas, coal, and electricity—across industrial and residential consumer categories, as detailed in (IEA, 2020). It takes into account the prices faced by end-users, including both non-tax components—like generation costs, network charges, and profit margins—and taxes, such as excise taxes and value-added taxes. To neutralize the effect of inflation, nominal prices are adjusted using country- and consumer-specific price indices. Our chosen price index effectively reflects the cross-country and temporal variations attributable to differences in regulatory, tax, market conditions, or consumer behaviors. We apply it as a control in both the final energy and electricity consumption models. While using an energy price index in the electricity model may introduce noise from other energy carriers, we retain it for two reasons: it sufficiently reflects variations in electricity costs, and comprehensive electricity price indices accounting for complex retail structures are limited.

5.4.2. Control variables

In estimating the energy consumption function, we control for three variables. The number of HDD per country per year serves as an exogenous control variable, sourced from the ODYSSEE database (Enerdata, 2023b), which is particularly pertinent to the residential sector due to its dependency on ambient temperatures and heating requirements (Hart and de Dear, 2004). To account for significant historical events that likely influenced energy consumption patterns, we also include two dummy variables: one representing the 2008 financial crisis and another for the 2020 COVID-19 pandemic. These variables are essential in acknowledging the distinct and significant impacts these events had on energy usage. Moreover, for the industrial sector, we account for the share of free emission allowances within the EU ETS (EEA, 2024). This metric, calculated as the ratio of free allowances a country receives to its total allocated allowances, serves to gauge the extent to which the sector is financially motivated to reduce emissions. This approach directly reflects the degree of incentive for industries to adopt emission-reducing practices based on the allocation of free allowances.

5.4.3. Mediating variables

Our analysis explores the indirect effects of digitalization on energy consumption through two mediating factors: the economic structure, particularly within the industrial sector, and energy efficiency across the industrial, transportation, and residential sectors. This section details the methods for quantifying economic structure and energy efficiency at a sectoral level, and the rationale behind choosing these variables as mediators.

Understanding the varied energy consumption profiles across different economic structures, such as industry-heavy versus service-oriented economies, is essential due to their differing levels of energy intensity and efficiency. These structural distinctions are key to analyzing energy consumption and act as a crucial mediator in the relationship between digitalization and energy usage, given that the integration of ICT capital can lead to varied effects depending on the economic context. The literature has proposed various methods to measure these economic structures. Lin and Huang (2023) suggest using the share of industrial value-added in GDP as an indicator of industrial structure, while Xu et al. (2022) develop an industrial distortion index based on the Euclidean distance between the output value share and employment share within an economy. Additionally, Ren et al. (2021) measure industrial upgrading through the ratio of output value between tertiary and secondary industries. These approaches aim to quantify the economic structure but may simplify the complex dynamics inherent in how economies organize their production activities, possibly neglecting the nuanced ways in which economies operate.

In this paper, we measure the structural change within the industry sector using the economic complexity index (ECI), which maintains information about the sector by applying dimensionality reduction (Hidalgo, 2021). The ECI captures the diversity and sophistication of production, offering a nuanced view of how structure of the industry sector might influence its energy consumption patterns. Specifically, the ECI measures "how diversified and complex an export basket is" (GLaHU, 2023), reflecting the intricacy of production processes and the potential for energy efficiency improvements. As control variables for ECI, we use the patents per capita and average school years in a country (UNDP, 2022, WIPO, 2023).

Identifying an appropriate metric for energy efficiency, defined as the optimal utilization of energy for delivering specific services or functions, presents a significant challenge due to the difficulties in precisely defining and measuring efficiency (Hunt and Ryan, 2015). Hunt and Ryan (2015) criticize the use of energy intensity as a somewhat coarse measure. Therefore, we leverage the ODEX energy efficiency index, which provides detailed metrics for energy efficiency within the EU's end-use energy sectors, including individual sectors and the aggregate economy from the ODYSSEE database, supported by the European Commission (Enerdata, 2023b, Lapillonne, 2020). ODEX offers a sector-specific gauge of energy efficiency advancements across different end-uses like lighting, heating, and cooking in the residential sector, as well as unit consumption across twelve industrial sectors, and improvements in vehicle efficiency and transport optimization in the transportation sector. Our research argues that digitalization plays a pivotal role in enhancing energy efficiency, promoting the adoption of smarter and more efficient energy use practices across these sectors, thereby underscoring the importance of digital technologies in driving energy conservation efforts.

5.5. Results

This results section is structured as follows: Initially, Section 5.5.1 explores the impact of digitalization on overall energy and electricity usage. Then, Section 5.5.2 delves into sector-specific analyses, examining the relationship between digitalization and energy and electricity consumption within the industrial, transport, and residential sectors. Lastly, Section 5.5.3 assesses the indirect effects of digitalization through mediating variables such as economic complexity and energy efficiency.

5.5.1. Digitalization's effect on aggregate energy and electricity consumption

Table 5.1 presents the results for aggregate energy and electricity consumption. Columns (1) and (3) correspond to equation (5.2), and columns (2) and (4) correspond to equation (5.3). We examine the impacts of digitalization on energy and electricity consumption across the EU-28, employing a dynamic specification estimated with the one-step system GMM estimator.[35]

For energy consumption, column (1) of Table 5.1 demonstrates a strong persistence in energy use, as evidenced by the lagged dependent variable coefficient (L.dep) of 0.818, significant at the 1% level. This implies that past energy consumption is a strong predictor of current consumption. Additionally, GDP per capita has a positive and significant effect (0.113 at 1% significance level), indicating that higher economic activity is linked to increased energy consumption. Specifically, a 1% increase in GDP per capita corresponds to an average increase of 0.113% in energy consumption. The negative coefficient for real energy prices suggests that higher prices result in reduced energy consumption. The HDD variable, representing weather-related energy needs such as heating, shows a positive and significant effect, while both the financial crisis and COVID-19 dummies have negative impacts, reflecting reduced consumption during these periods. Regarding electricity consumption, column (3) has similar findings with a slightly lower persistence (0.785 at 1% significance level), indicating that previous electricity use is also a key predictor of current use. The impacts of GDP per capita, energy prices, HDD, and the two crises on electricity consumption are consistent with those observed for overall energy consumption.

Columns (2) and (4) reveal that investments in ICT capital exhibit a negative correlation with energy consumption, with coefficients of -0.074 for energy and -0.047 for electricity, significant at the 5% and 10% levels, respectively. This indicates that an increase in ICT capital is associated with reductions in both energy and electricity consumption within the EU-28. These reductions can be attributed to several interconnected factors: efficiency gains in production and consumption, the rising importance of services-oriented activities which often leads to a less energy-intensive economic structure, advancements in automation and control, and improvements in user guidance. The lower significance may reflect its nature as a stock variable, which overlooks changes in capital utilization. For comparison, Appendix D.2 presents estimations using ICT capital compensation (a flow variable) and a societal digitalization index. The robustness checks show that ICT capital share captures the same directional effect but partially underestimates digitalization's impact on energy consumption. Because final energy consumption does not reflect useful work, Appendix D.5 provides estimates using final exergy consumption as the dependent variable .

5.5.2. Digitalization's effect on disaggregate energy and electricity consumption

This section explores the relationship between digitalization and energy and electricity consumption across specific end-use sectors: industry, transport, and

[35]The two-step system GMM estimates are provided in Appendix D.4.

Table 5.1.: The effect of digitalization on aggregate energy and electricity consumption.

Variable	Energy		Electricity	
	(1)	(2)	(3)	(4)
L.dep	0.818***	0.739***	0.828***	0.850***
	(0.05)	(0.08)	(0.07)	(0.08)
Digitalization		-0.074**		-0.047*
		(0.04)		(0.03)
GDP per capita	0.113***	0.105***	0.095**	0.068*
	(0.03)	(0.03)	(0.04)	(0.04)
Energy price	-0.310***	-0.356***	-0.197***	-0.242***
	(0.04)	(0.04)	(0.05)	(0.05)
HDD	0.078***	0.116***	0.038**	0.041**
	(0.02)	(0.04)	(0.02)	(0.2)
Fin. crisis	-0.067***	-0.066***	-0.072***	-0.076***
	(0.01)	(0.01)	(0.01)	(0.01)
COVID	-0.084***	-0.077***	-0.061***	-0.057***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-0.081	0.017	-0.108	-0.006
	(0.11)	(0.19)	(0.17)	(0.16)
AR(2)	0.288	0.334	0.118	0.122
Hansen test	18.68	21.48	21.92	21.41
P-value	0.229	0.369	0.110	0.373
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The “P-value” is reported for Hansen tests.

residential. The results of these sector-specific estimations are presented in Table 5.2.

The effect of digitalization on energy and electricity consumption exhibits distinct patterns across the industry, transport, and residential sectors, suggesting nuanced associations between the adoption of digital technologies and energy use. In terms of energy consumption, digitalization is associated with a reduction in the industry sector, as indicated by a statistically significant negative coefficient, reflecting efficiency gains and possibly structural shifts towards less energy-intensive processes. However, in the transport sector, the relationship between digitalization and energy consumption is not statistically significant, suggesting the current level of digitalization does not clearly impact energy use within this sector. In contrast, the residential sector shows a statistically significant negative association, indicating digital technologies' substantial role in reducing energy consumption, likely through enhanced home energy efficiency and smarter management systems. When examining electricity consumption, digitalization also shows a negative correlation in the industry sector. The effect in the transport sector remains statistically insignificant, suggesting a minimal impact of digitalization on electricity use within this sector. Conversely, the residential sector demonstrates a slight but significant negative correlation, pointing towards the beneficial role of digitalization in reducing electricity consumption, possibly through the adoption of energy-efficient appliances and smarter energy management practices. Overall, these results suggest that digitalization has a statistically significant impact on reducing energy consumption in the industry and residential sectors. In contrast, its influence on the transport sector and electricity consumption in general is less pronounced.

Our analysis also indicates variations in how control variables affect energy and electricity consumption in different sectors. Economic activity is positively associated with energy consumption in all three sectors, with coefficients indicating a stronger effect in the industry sector, and a slightly weaker, but still positive, effect in the transport and residential sectors. This positive relationship likely stems from higher production activities in the industry and transport sectors and increased consumption in residential areas. This also aligns with the positive sign and magnitude of elasticity obtained by other studies (e.g., Alberini and Filippini, 2011, Cialani and Mortazavi, 2018). Energy prices negatively affect energy consumption in all sectors, with the strongest impact observed in transport (-0.293 significant at the 1% level), followed by industry (-0.246 significant at the 1% level) and residential (-0.106 significant at the 5% level). This indicates a typical demand response to price increases, wherein higher energy costs lead to reduced consumption. For example, a 1% increase in real energy prices is associated with lower energy consumption in the transport sector by 0.293%, on average. Additionally, HDD positively affects energy consumption across all sectors, most notably in the residential sector, reflecting the increased need for heating due to colder temperatures. Regarding electricity consumption, our analysis reveals that economic activity is again positively associated with consumption in the industry sector, albeit with a weaker effect than its impact on overall energy consumption, and only marginally in the transport and residential sectors. The impact of energy prices on electricity consumption is also negative across sectors, most notably in industry but not statistically significant in transport and residential sectors. This finding aligns with the results obtained by Cialani and Mortazavi (2018), who also find that residential electricity consumption is less sensitive to price changes than the industrial sector.

We also control for the share of free allowances under the EU Emissions Trading System (ETS) on the energy consumption of the industry sector, as detailed in column (2). Including free allowances as a control variable considers the potential impact of regulatory incentives on energy consumption behaviors within industries. Free allowances could theoretically lower CO_2 emission costs, potentially diminishing firms' financial incentive to reduce energy consumption. The estimated coefficient for the share of free allowances is positive and statistically significant, indicating a positive association with energy consumption in the industry sector. This suggests that industries with a higher share of free allowances tend to consume more energy, likely because the economic incentive to reduce energy usage or invest in more energy-efficient technologies is lessened by the availability of these allowances. We also find that the results related to the effect of digitalization on energy consumption remain statistically significant, suggesting that the efficiency gains and potential structural shifts towards less energy-intensive processes attributed to digitalization are not significantly confounded by the regulatory context represented by the allocation of free allowances.

HDD shows a strong positive correlation with energy consumption in all sectors, particularly in the residential sector, indicating increased energy use during colder periods. This trend is also observed in electricity consumption, albeit to a lesser degree. The financial crisis exerts a significant negative effect on energy consumption, particularly in the industry and transport sectors. This suggests a reduction in energy usage, possibly due to decreased economic activity or the implementation of cost-saving measures. The impact of the COVID-19 pandemic varies; it has resulted in a notable decrease in energy and electricity consumption in the industry and transport sectors possibly due to reduced economic and travel activities. In contrast, it leads to increased electricity consumption in the residential sector, likely reflecting the shift to working and spending more time at home. Collectively, these variables highlight how external factors like weather conditions, economic disruptions, and global crises can significantly alter energy and electricity consumption patterns in different sectors.

Lastly, our findings indicate a positive and significant dynamic effect of the lagged dependent variable on electricity and energy consumption across all three sectors. This finding suggests that past consumption patterns have a persisting and reinforcing impact on current energy and electricity usage. Such a trend highlights the role of historical consumption trends in forecasting future energy demands, demonstrating gradual evolution in consumption patterns rather than abrupt shifts within the observed sectors.

Building on these insights, the subsequent section examines the mediating effects of efficiency measures between ICT capital accumulation and energy and electricity consumption across the industry, transport, and residential sectors. We also explore the role of economic structure in the industry sector as a mediating factor.

5.5.3. Digitalization's indirect effects on energy and electricity consumption

This section follows the methodology outlined in Section 5.3.3. Table 5.3 presents the results of the first step, involving the estimation of equation (5.6), which

Table 5.2.: The effect of digitalization on disaggregate energy and electricity.

(a) Columns (1)-(4) for energy consumption.

Variable	Energy			
	(1)	(2)	(3)	(4)
	Industry	Industry	Transport	Residential
L.dep	0.821***	0.808***	0.712***	0.689***
	(0.07)	(0.07)	(0.10)	(0.06)
Digi.	-0.041**	-0.039*	-0.024	-0.267*
	(0.02)	(0.02)	(0.15)	
Econ. act.	0.186**	0.174**	0.114**	0.122*
	(0.09)	(0.09)	(0.04)	(0.07)
Energy price	-0.246***	-0.308***	-0.293***	-0.106**
	(0.09)	(0.08)	(0.07)	(0.05)
Free Allowances		0.040**		
		(0.02)		
HDD	0.129***	0.142***	0.040**	0.207***
	(0.04)	(0.04)	(0.02)	(0.04)
Fin. crisis	-0.144***	-0.156***	-0.054***	0.010
	(0.02)	(0.02)	(0.02)	(0.01)
COVID	-0.039***	-0.031**	-0.141***	0.007
	(0.01)	(0.02)	(0.01)	(0.01)
Constant	-0.897**	-0.913**	0.246	-1.241***
	(0.40)	(0.39)	(0.17)	(0.35)
AR(2)	0.235	0.197	0.182	0.791
Hansen test	23.21	23.42	25.09	27.47
P-value	0.279	0.268	0.198	0.123
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector.

shows the impact of digitalization on the mediating variables across the three sectors. Subsequently, Table 5.4 provides the estimated effect of digitalization on sectoral energy and electricity consumption, as derived from equation (5.7). Building on the results from these initial steps, we then compute the indirect effects using the estimated coefficients.

(b) Columns (5)-(7) for electricity consumption.

Variable	Electricity		
	(5)	(6)	(7)
	Industry	Transport	Residential
L.dep	0.820***	0.903***	0.909***
	(0.14)	(0.07)	(0.03)
Digi.	-0.020**	-0.004	-0.060*
	(0.00)	(0.03)	
Econ. act.	0.100*	0.008*	0.039*
	(0.06)	(0.00)	(0.02)
Energy price	-0.136**	-0.015**	-0.018
	(0.05)	(0.01)	(0.05)
HDD	0.066*	0.006	0.015*
	(0.04)	(0.00)	(0.01)
Fin. crisis	-0.091***	-0.003**	0.002
	(0.01)	(0.00)	(0.01)
COVID	-0.037***	-0.005***	0.010**
	(0.01)	(0.00)	(0.01)
Constant	-0.432	-0.039	-0.113
	(0.32)	(0.03)	(0.11)
AR(2)	0.836	0.051	0.839
Hansen test	20.38	22.21	17.24
P-value	0.434	0.965	0.370
Obs.	364	364	364
Countries	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The “P-value” is reported for Hansen tests. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector.

Table 5.3 shows digitalization's effect on the potential mediating variables in industry, transport, and residential sectors. In the industry sector, digitalization negatively impacts the economic complexity index, indicating that an increase in ICT capital share could be associated with a shift towards less complex, possibly more service-oriented activities that traditionally exhibit lower energy intensity. This could suggest that as industries adopt more digital technologies, there is a structural transformation towards activities that are less reliant on physical inputs and energy consumption. The effect of digitalization on energy efficiency in the industry sector is positive and statistically significant at the 10 % level, indicating that investments in ICT within the industry sector are associated with improvements in energy efficiency. However, our results reveal that the effect of digitalization on energy efficiency within the transport sector is not statistically significant, implying that the direct relationship between increased ICT capital and efficiency gains might be complex or delayed. For the residential sector, the positive impact of digitalization on efficiency points towards the adoption of ICT technologies leading to more energy-efficient household operations. This could be through smarter energy management systems, more efficient appliances, or behaviors induced by greater awareness and control over energy consumption facilitated by digital technologies.

Table 5.3.: Effects of digitalization on the mediating variables per sector.

Variable	Industry		Transport	Residential
	(1)	(2)	(3)	(4)
	Structure	Efficiency	Efficiency	Efficiency
L.dep	0.803***	0.927***	1.029***	0.945***
	(0.08)	(0.02)	0.06	(0.03)
Digitalization	-0.047**	0.009*	-0.011	0.070*
	(0.02)	(0.02)	(0.01)	(0.04)
Economic activity		-0.077***	0.042*	0.048**
		(0.02)	(0.02)	(0.02)
Energy price	-0.119	0.003	0.124***	0.082***
	(0.08)	(0.03)	(0.06)	(0.02)
Free allowances		-0.020***		
		(0.01)		
HDD		-0.001	-0.008	
		(0.01)	(0.01)	
Financial crisis	0.029*	-0.011***	0.006	0.013***
	(0.02)	(0.00)	(0.01)	(0.00)
COVID	-0.014	-0.007***	0.001	0.001
	(0.01)	(0.00)	(0.00)	(0.00)
Patents	0.054**			
	(0.02)			
School	0.379**			
	(0.17)			
Heat policy				-0.001
				(0.00)
Appliance policy				-0.002
				(0.00)
Constant	-0.733**	0.251***	-0.177**	-0.190***
	(0.34)	(0.07)	(0.08)	(0.07)
AR(2)	0.539	0.084	0.632	0.958
Hansen test	26.28	15.90	23.18	16.56
P-value	0.157	0.784	0.280	0.167
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests. The economic activity measures are the GDP per capita for industry and transport, and the private consumption in the residential sector. The structure measure is economic complexity. The efficiency (i) is the ODEX index of the industry, the traffic of goods per capita, and the ODEX index of the residential sector. The efficiency (ii) is the traffic of passengers per capita.

Table 5.4.: Effects of the mediating variables on energy and electricity consumption per sector.

(a) Columns (1)-(3) for energy consumption,

Variable	Energy		
	(1)	(2)	(3)
	Industry	Transport	Residential
L.dep	0.716***	0.764***	0.592***
	(0.08)	(0.09)	(0.09)
Structure	0.187*		
	(0.10)		
Efficiency	-0.325***	0.013	-0.269***
	(0.11)	(0.12)	(0.11)
Digi.	-0.011	-0.024	-0.157
	(0.02)	(0.03)	(0.12)
Economic activity	-0.013	0.098***	0.166**
	(0.11)	(0.04)	(0.08)
Energy price	-0.326***	-0.345***	-0.125*
	(0.10)	(0.08)	(0.07)
Free Allowances	0.012		
	(0.03)		
HDD	0.120***	0.028**	0.257***
	(0.04)	(0.01)	(0.05)
Fin. crisis	-0.168***	-0.060***	-0.009
	(0.02)	(0.02)	(0.01)
COVID	-0.019	-0.154***	0.013
	(0.02)	(0.02)	(0.01)
Constant	-0.193	0.254*	-1.508***
	(0.47)	(0.15)	(0.42)
AR(2)	0.447	0.116	0.509
Hansen test	19.49	17.77	26.40
P-value	0.362	0.275	0.153
Obs.	364	364	364
Countries	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector. The structure measure is economic complexity. The efficiency is the ODEX index of the industry, transport, and residential, respectively.

(b) Columns (4)-(6) for electricity consumption,

Variable	Electricity		
	(4)	(5)	(6)
	Industry	Transport	Residential
L.dep	0.875***	0.922***	0.885***
	(0.06)	(0.08)	(0.04)
Structure	0.076*		
	(0.04)		
Efficiency	-0.025	0.004	-0.084**
	(0.05)	(0.00)	(0.01)
Digi.	0.001	0.000	-0.003
	(0.01)	(0.00)	(0.00)
Economic activity	0.005	0.005	0.063**
	(0.02)	(0.00)	(0.03)
Energy price	-0.106***	-0.013**	-0.008
	(0.04)	(0.01)	(0.06)
HDD	0.014	0.005	0.016*
	(0.02)	(0.00)	(0.01)
Fin. crisis	-0.100***	-0.003**	-0.003
	(0.01)	(0.00)	(0.01)
COVID	-0.035***	-0.005**	0.014***
	(0.01)	(0.00)	(0.01)
Constant	0.032	-0.029	-0.150*
	(0.13)	(0.04)	(0.09)
AR(2)	0.769	0.050	0.873
Hansen test	20.92	17.27	15.35
P-value	0.283	0.303	0.427
Obs.	364	364	364
Countries	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector. The structure measure is economic complexity. The efficiency is the ODEX index of the industry, transport, and residential, respectively.

Table 5.4 details the effects of mediating variables on energy and electricity consumption across sectors. In the industry sector, our results indicate that digitalization's influence on energy consumption is mediated by both changes in economic complexity and improvements in energy efficiency. However, the anticipated mediation effect of digitalization through energy efficiency does not hold for the electricity consumption, as shown in column (4). A potential explanation for this result is that our measure of energy efficiency encompasses all energy carriers, within which electricity plays a comparatively minor role. In the transport sector, while efficiency does not appear to significantly mediate the effect of digitalization on energy consumption, it indicates a relatively stable interaction between digitalization, energy efficiency, and energy use in this sector. Finally, in the residential sector, efficiency plays a statistically significant mediating role, highlighting how improvements in energy efficiency can significantly influence the impact of digitalization on energy and electricity consumption. This efficiency-driven mediation suggests that as residential spaces become more digitized, energy-efficient technologies and practices become crucial in determining overall energy and electricity usage.

The mediation analysis indicates potential mediation in the industry and residential sector, while there is no evidence for mediation in the transport sector. In the third step of the analysis the indirect effect is computed using the product method. In the industry sector, digitalization's influence on energy consumption is mediated by economic complexity and energy efficiency. The indirect effects of digitalization on energy and electricity consumption through economic complexity are -0.009 and -0.004, respectively. Additionally, the indirect effect of the ICT capital share through energy efficiency on the energy consumption in the industrial sector is -0.003. Our results also suggest that energy efficiency is a mediating factor in the residential sector, highlighting how improvements in energy efficiency can significantly influence the impact of digitalization on energy and electricity consumption. A 1% increase of digitalization decreases energy and electricity consumption through efficiency improvements by 0.019% and 0.006%, respectively. This efficiency-driven mediation suggests that ICT-capital could contribute to a more efficient use of energy and electricity in residential spaces. In the transport sector, no significant effect of digitalization on efficiency nor of efficiency on energy consumption can be found.

5.6. Discussion

In the preceding section, we demonstrated that digitalization within the EU-28 is associated with reduced energy and electricity consumption over the past decade. These results are in line with previous findings on the energy-saving impacts of ICT, as reported by Xu et al. (2022), Schulte et al. (2016), and Han et al. (2016). Our research contributes further by exploring the sectoral effects of digitalization, especially within the industry, transport, and residential sectors, and by considering sector-specific mediating factors that could influence the relationship between digitalization and energy consumption.

In the context of the industry sector, our findings indicate that digitalization is negatively associated with energy and electricity consumption. This negative association suggests a transformative shift towards less energy-intensive operations, potentially facilitated by the integration of advanced technologies that enhance energy efficiency and increased emphasis on service-oriented activities. Through mediation analysis, we explore how this effect is predominantly mediated by enhancements in energy efficiency and changes in the economic structure. Specifically, our results reveal that digitalization correlates with improvements in energy efficiency. The positive association between ICT capital share and energy efficiency is in line with Matthess et al. (2023), who also find a positive impact of digitalization on energy intensity in the industry sector across EU countries. Regarding the mediation effect through economic complexity, we observe that greater investments in ICT are linked with a structural transition towards products with lower economic complexity, which are inherently associated with reduced energy demands. This observation supports the hypothesis that sectors of lower economic complexity are less energy-intensive. For example, Crozet and Milet (2017) illustrate this shift by examining French manufacturing firms, noting that a significant number have augmented their service output, indicating an internal restructuring trend within the firms themselves.

In the transport sector, our empirical analysis reveals that the influence of digitalization on energy consumption, as well as its potential to enhance energy efficiency, does not reach statistical significance. This finding suggests that, within the timeframe and context of our study, digitalization has not yet led to measurable reductions in energy consumption or significant improvements in energy efficiency in this sector. A potential interpretation could be related to the inherent characteristics and challenges of the transport sector, including the slow turnover rate of infrastructure and vehicles, and the potential for rebound effects where efficiency gains lead to increased usage rather than reduced energy consumption (Waisman et al., 2013, Zito and Salvo, 2011). Another interpretation could be that energy savings in the transport sector may instead originate from increased ICT capital shares in other sectors, such as industry and residential, e.g., digital infrastructure to promote remote work or smartphones and apps for road navigation (Lange et al., 2020).

In the residential sector, our analysis reveals that digitalization is significantly associated with reduced energy consumption, particularly through enhanced heating efficiency. This potential role of efficiency in heating could be explained by the exponential growth in smart thermostat installations across EU homes, escalating from 1 million in 2014 to 22 million by 2020. These devices enable more efficient heating strategies, for instance, heating solely occupied rooms or discontinuing heating when windows are open. For example, LeanHeat's application of such sensor and control systems in 80,000 apartments in Finland has achieved energy cost savings of 10-20% for building owners (Lyons et al., 2019). In contrast, the influence of digitalization on electricity consumption, while still present, is less pronounced. This lesser impact could be partly attributed to the fact that ICT devices and infrastructure themselves consume electricity, potentially offsetting efficiency gains in other areas. This suggests that while digitalization broadly curtails overall energy use, its effect on electricity consumption is moderated by the electrical demand of digital technologies, indicating that significant energy savings are primarily in non-electric energy forms, such as heating fuels (Gao et al., 2023, Pothitou et al., 2017).

5.7. Conclusion

This paper explores the impact of digitalization on final energy and electricity consumption across the EU-28 from 2007 to 2020, focusing on the industry, transport, and residential sectors. By disaggregating energy consumption into these end-use sectors, our study identifies sector-specific mediation factors influenced by structure and efficiency.

Our findings reveal that, at an aggregate level, digitalization—measured by the share of ICT capital— is generally associated with lower energy and electricity consumption. However, this overarching trend manifests differently across sectors. Specifically, in the residential sector, digitalization plays a significant role in enhancing energy efficiency, directly contributing to lower energy consumption. In the industry sector, observed decrease in energy usage is due to efficiency gains and a shift toward activities of lower economic complexity. These activities inherently require less energy, suggesting that digitalization's impact on energy consumption extends beyond just efficiency improvements to include structural changes in economic activities that are intrinsically less energy-intensive. In the transport sector, our analysis shows that the effects of digitalization on reducing energy consumption and improving energy efficiency lack statistical significance. A potential reason could be the slow turnover of infrastructure and vehicles and the susceptibility to rebound effects in the transport sector could prevent digitalization from being effective in the considered time period.

Our analysis could inform both academic research and policy development highlighting the benefit of sector-specific analyses in energy consumption studies. Such a distinct approach allows decision-makers to take sector-specific digitalization and energy consumption characteristics into consideration. Our findings suggest that promoting digital technologies in the residential sector could contribute to achieving energy consumption reduction goals. Therefore, encouraging the use of smart controls for efficient heat and electricity management could be a straightforward complement to building renovation and heating system replacement. Similarly, promoting the use of ICT applications to enhance manufacturing processes could lead to energy savings in the industrial sector. The decrease in industrial energy consumption is also found to be linked to a shift towards less energy-intensive activities, which warrants closer attention on the actual structural changes accompanying digitalization. Depending on the value of the emerging services and potentially declining energy-intensive activities, guiding policies could be considered. In the transport sector, research could be conducted on digitalization effects over longer time horizons, and with consideration of cross-sector effects of ICT capital shares to determine whether digitalization's impact outside the transport sector exceeds its effect within it.

A limitation of our study is the reliance on low-frequency data, which inherently comes with low variation in price and other variables. This characteristic likely contributes to the relatively small estimates of elasticities observed in our analysis. The primary reason for our approach was the limited availability of ICT capital data and economic activity variables at a higher frequency. Future research could explore higher frequency data and longer time horizons. Our robustness checks suggest that incorporating economic flow measures of digitalization into exergy models could be a promising avenue.

A. Supplementary Material for Chapter 2

A.1. Regression Results

The regression results for the day-ahead market are illustrated in Figure A.1. Based on the data for the years 2015-2019, a function is fitted to each month of the year.

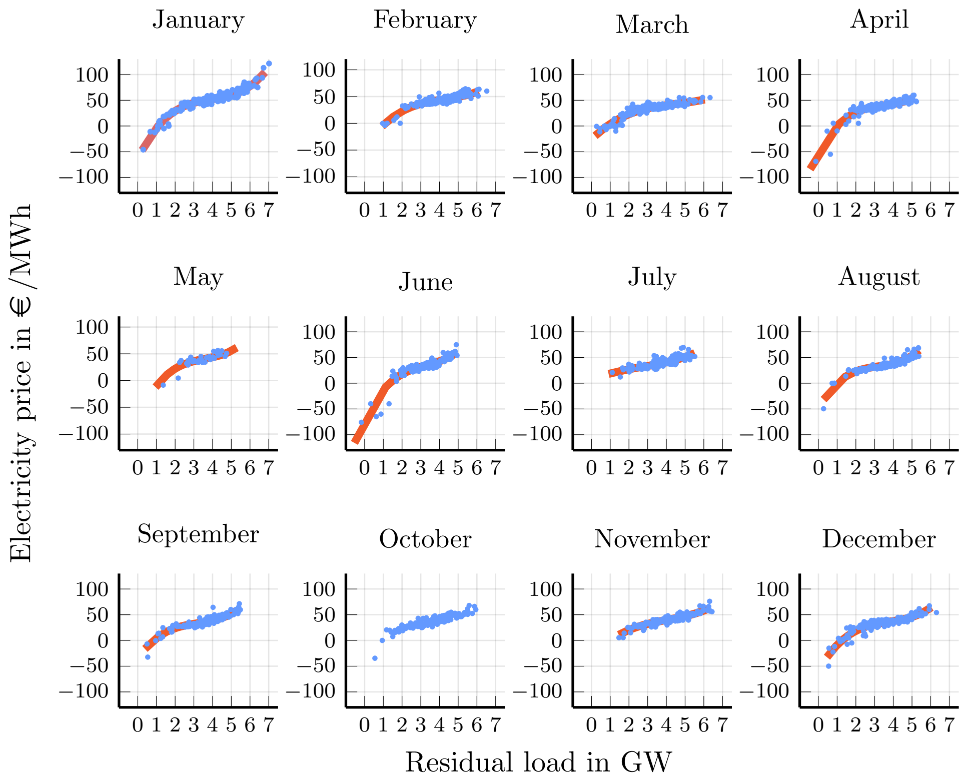

Figure A.1.: Regression results for the day-ahead market.

Analogously, the intraday market prices are regressed on the day-ahead market prices and the wind generation forecast error. Table A.1 shows the regression results indicating that the applied independent variables are significant within this model.

Table A.1.: Regression results for the intraday market.

	Coef.	Std. Error	t	$\Pr(>\|t\|)$	Lower 95%	Upper 95%
(Intercept)	1.8026	0.1922	9.38	$< 1e-20$	1.4258	2.1793
DA prices	0.9717	0.0046	211.68	$< 1e-99$	0.9627	0.9807
Forecast error	-0.9768	0.0194	-50.31	$< 1e-99$	-1.0149	-0.9388
(Forecast error)^2	-0.0221	0.0023	-9.56	$< 1e-20$	-0.0266	-0.0175

A.2. Monte Carlo simulation

To obtain synthetic electricity market price time series for both the day-ahead and the intraday market, we generate synthetic time series of the independent variables used in the parametric models of the electricity market, i.e., wind generation forecast and wind generation forecast errors. We follow Papaefthymiou and Klockl (2008) by parameterizing the transition probabilities of a Markov chain with 15 states on both parameters separately. Note that we do not consider the correlation between the parameters. However, we use the relative forecast errors instead of the absolute ones so that the absolute errors still scale with the wind generation forecast. The transition probability matrix includes the probabilities to change from one state to another to the next period. We obtain a cumulative distribution function of possible following states for every state.

For each time step of the simulation horizon, we draw random numbers from a uniform distribution $\mathcal{U}(0,1)$. Plugging the random number into the inverse of the cumulative distribution function obtains the next state within the Markov chain (Amelin, 2004). We continue the process for the entire simulation horizon and repeat it for the number of samples we generate. The day-ahead prices are then calculated based on Equation (2.7). Figure 2.3 shows the range of resulting price duration curves. The intraday prices are computed based on Equation (2.8), also using the synthetic day-ahead prices. The results are shown in Figure 2.3.

A.3. Annuity

The annuity of the electrolyzer investment is computed based on equation (A.1). Multiplying the CAPEX with the capital recovery factor obtains the annuity.

$$\text{annuity} = CAPEX * \frac{(1+i)^n * i}{(1+i)^n - 1} \tag{A.1}$$

A.4. Notation

Table A.2.: Model indices, parameters, and variables.

Name	Unit	Definition
Sets		
$t, j \in T$		Time periods
$m \in M$		Electricity markets (intraday, day-ahead)
Parameters		
p^{H2}	EUR/kg	Green hydrogen selling price
p^{DA}	EUR/$\mathrm{MWh_{el}}$	Day-ahead price
p^{ID}	EUR/$\mathrm{MWh_{el}}$	Intraday price
p	EUR/$\mathrm{MWh_{el}}$	Electricity price
δ	-	Time scaling
cap	$\mathrm{MW_{el}}$	Electrolyzer capacity
α	EUR/$\mathrm{MWh_{el}}$	Electricity price surcharges
β	-	Minimal load as a fraction of the capacity
γ	-	Simultaneity of electricity production and consumption
σ	-	Capacity ratio of electrolyzer and RE plant
re	-	(current) RE capacity factor
q^{res}	$\mathrm{MW_{el}}$	Residual load
n	a	Years
Variables		
$Contribution$ $margin$	EUR	Total contribution margin
R	EUR	Revenue
C	EUR	Cost
C^{FOM}	EUR	Fixed operation and maintenance cost
C_t	EUR	Variable cost
Q	kg	Hydrogen production
L	$\mathrm{MW_{el}}$	Load
B	-	Binary variable to determine whether plant is switched on/off
FE	-	Forecast error

B. Supplementary Material for Chapter 3

B.1. Notation

Table B.1.: 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 B.2.: 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 B.3.: 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	
$U^R_{c,s}$	Random utility from charging product c in charging event s
$U^N_{c,s}$	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

B.2. Data

B.2.1. Segments

The case study examines three segmentations, *Area*, *Activity*, and *Charger*. Table B.4 lists the segments of each segmentation and their assignment rule.

Table B.4.: Segmentations applied in the case study and their assignment rules.

Segmentation	Segment	Assignment rule	Source
Area	Urban	71 Urban region - metropolis 72 Urban region - regional center and metropolis	BBSR (2023)
	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 Customer parking lot Parking garage Park & Ride Other	NCfCI (2024)
	Refueling	Petrol station on a federal highway Other filling station	
Charger	AC	$q < 50kW$	
	DC	$q \geq 50kW$	

B.2.2. 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_s^o. 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 B.2.3. 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 (Li et al., 2020, Watson, 2022). B.2.4 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 B.2.4.

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

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 $p^{Block} * t$. B.2.5 provides an overview of blocking fees. Some blocking fees have a limit, $\overline{t}^{Block}$, beyond which the blocking fee does not increase anymore.

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

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 B.2.5.

B.2.3. 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.1 illustrates the resulting battery size distribution. The mean capacity is 73 kWh.

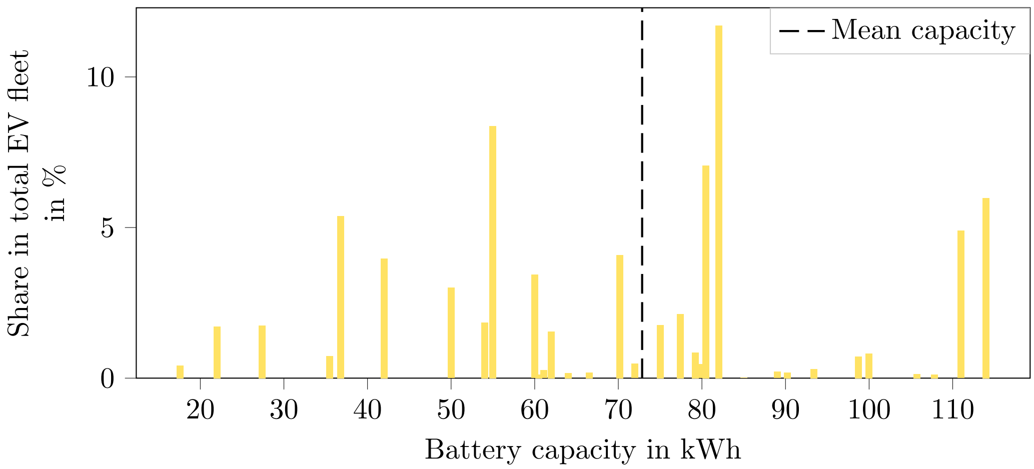

Figure B.1.: The distribution of battery capacities in the German car fleet in the year 2023 based on KBA (2024) and ADAC (2024).

B.2.4. 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.2 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).

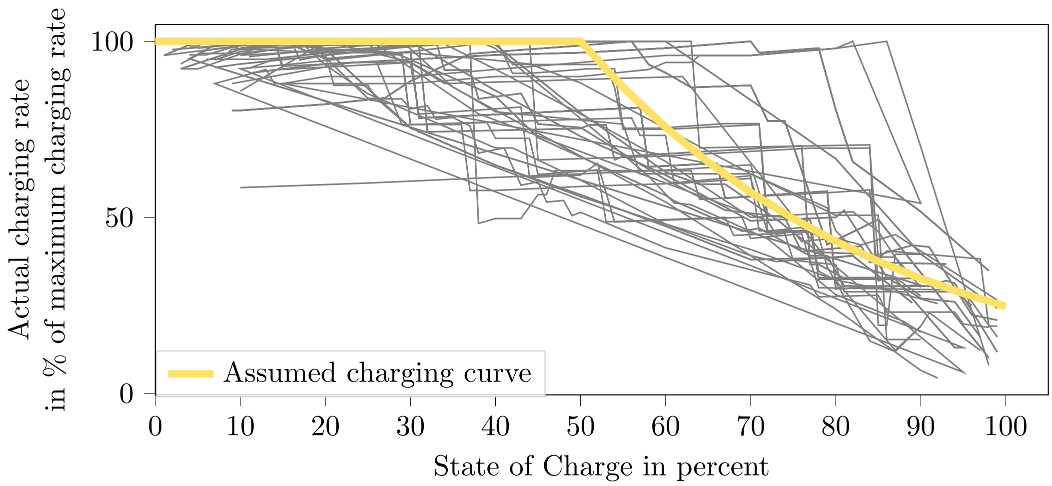

Figure B.2.: Observed charging curves depending on the SoC based on Fastned (2025) and Schaden et al. (2021).

B.2.5. Blocking fee

Several German charging point operators charge a blocking fee for parking at a connection point (e.g. BMW, 2025, Elli, 2025, ENBW, 2024, Entega, 2025, EWE go, 2025, ADAC, 2025, IONITY, 2025, Lichtblick, 2025, MAINGAU, 2025, Mercedes, 2025, Sachsenenergie, 2025, Shell, 2024, SWD, 2024, SWM, 2025). Figure B.3 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 €.

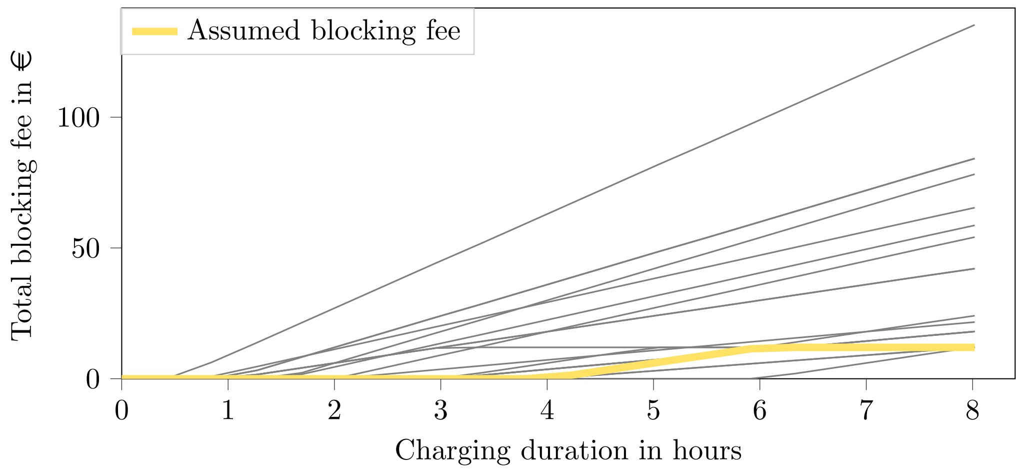

Figure B.3.: An overview of blocking fees applied in German charging tariffs depending on the parking duration.

B.3. 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.

B.3.1. Sample size

The case study comprises 8,000 observations, randomly selected from a dataset of 1.03 million charging sessions 3.4.1. 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 B.5 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 B.5 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.

B.3.2. 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 B.6, 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

Table B.5.: 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.

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 3.4.2). Table B.6 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 B.6.: 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.

B.3.3. 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 3.5.4. 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 B.7 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 B.7.: 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.

B.3.4. 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 B.8 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 3.5.2, 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 3.5.2 and the strong out-of-sample fit of the utility function including the higher-order terms shown in Section 3.5.1 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 B.8.: The correlation between parameters for the Quadratic-in-Parameter utility function with the interaction term with in column (5) of Table 3.3.

	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.

C. Supplementary Material for Chapter 4

C.1. Isocost curves

Figure C.1 illustrates the isocost curves of the household's decision problem. For illustrative purpose, the plots are based on the data of the numerical example, although the plots shall only provide an intuition about the properties of the household's decision context. The costs consist of the investment costs, fuel costs, and the chosen fph. Moreover, emission taxes or subsidies would affect the costs. The indifference curves would be horizontal lines, since the household's utility depends solely on the heat. In the left illustration of figure C.1, there are the basic isocost curves. The darker the color, the higher the costs. Without any policy intervention, higher fph can provide heat at lower costs, as the isocost curves are convex in fph. Emission taxes and subsidies can turn the course of the isocost curves so that they are decreasing with fph, and lower fphs can provide heat at lower costs.

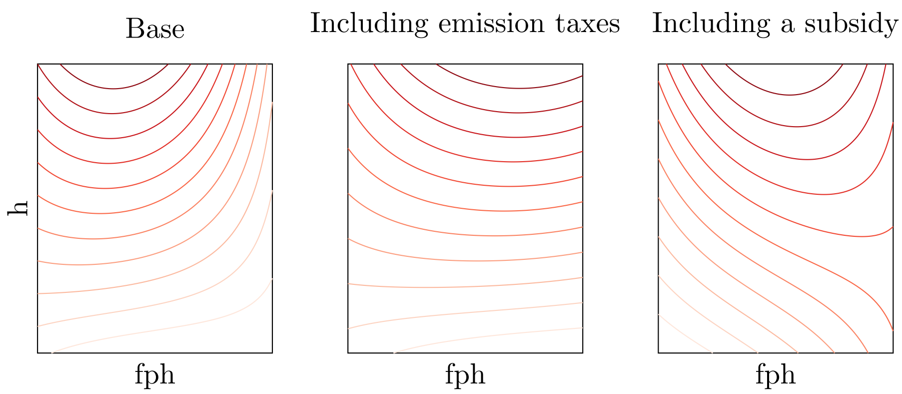

Figure C.1.: Illustration of the isocost curves of the household's decision problem. The darker the color, the higher the costs. The left plot shows the isocost curves of the original problem, the middle the isocosts under an emission tax rate, and the plot to the right the isocosts given a technology subsidy. The plots are based on the inputs of the numerical case study.

Without any policy intervention, for all temperature levels, higher fphs are the option with the lowest cost. The isocost curves show a steeper increase towards high fphs so that there is in any case a high fph alternative for each temperature level. Introducing an emission tax, decreases the slope of the isocost curves at the end of higher fphs, here additional cost for paying the emission tax are added to the total costs. With that, the slope at lower fph is higher so that for all temperature levels a lower fph constitutes the technology with the lowest costs. Analogously, a subsidy depending on the fph decreases the slope of the isocost curves at high fph. In contrast to the case of emission taxes, the effect does not scale with the chosen temperature level, so that for high temperature levels the shape remains similar to the case without subsidy, as the relative impact is lower. At low-temperature levels, the impact of the subsidy, however, is higher. The household can take the subsidy profit from the higher efficiency and reach higher temperature levels, or waive the subsidy and remain on lower temperature levels.

C.2. Proofs

C.2.1. Proof 1:

Proposition:
There does not exist any set of emission tax rates τ_t for all $t \in [1, ..., T]$ that leads to the first-best outcome fph^{opt} and h_t^{opt}.
Proof analogous to Heutel (2015):
Suppose the contradiction: there exists a set of tax rates $\tau_t^{opt\beta}$ that lead to $m_t^* = m_t^{opt}$ for all $t > 0$ and $gpm^* = gpm^{opt}$. The first-order condition for choice of m_t in period t is $U'(m_t^*) = (p_t(fph^*) + epf(fph^*) \cdot \tau_t^{opt\beta}) \cdot fph^*$ or $U'(m_t^{opt}) = (p_t(fph^{opt}) + epf(fph^{opt}) \cdot \tau_t^{opt\beta}) \cdot fph^{opt}$. Since U'' is strictly negative the only optimal solution, when $\beta = 1$, is $\tau_t^{opt\beta} = \tau_t^{pig}$. When $\beta < 1$, the optimal solution does not change, since the planner does not consider the quasi-hyperbolic discount factor, but first order conditions of the consumer change. Thus, it does not equal the planner's solution.

C.2.2. Proof 2:

Proposition:
If $\tau_t = \tau_t^{pig}$ for all $t \in [1, ..., T]$ and $\sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot [[p_t(fph^*) + epf(fph^*) \cdot \tau_t] + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^*]$ then $fph^* > fph^{opt}$ and $h_t^* < h_t^{opt}$ for all $t \in [1, ..., T]$.
Proof analogous to Heutel (2015):
Note that the consumer's choice of fph^* is given by her first-order condition; call this equation F:

$$
\begin{aligned}
F = & \\
& - c'(fph^*) - \beta \cdot \sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot \Big[\quad [p_t(fph^*) + epf(fph^*) \cdot \tau_t] \\
& \qquad\qquad + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^* \Big]
\end{aligned}
\tag{C.1}
$$

The implicit function theorem can be used to show how fph^* varies with β:

$$\begin{aligned}
&\frac{dfph^*}{d\beta} = \frac{-dF/d\beta}{dF/dfph} = \\
&\sum_{t=1}^{T} \delta^t \cdot h_t^* \\
&\cdot \Big[[p_t(fph^*) + epf(fph^*) \cdot \tau_t] + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^* \Big] \\
&\cdot \frac{1}{dF/dfph}
\end{aligned} \tag{C.2}$$

The denominator is negative from the second-order condition of the consumer's optimization problem. The numerator is positive (or zero) if

$$\begin{aligned}
\sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot \Big[\quad & [p_t(fph^*) + epf(fph^*) \cdot \tau_t] \\
& + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t] \cdot fph^* \Big] \geq 0
\end{aligned} \tag{C.3}$$

If the numerator is positive, then $dfph^*/d\beta < 0$. Since when $\beta = 1$ $fph^* = fph^{opt}$, it follows that in the case of $\beta < 1$ $fph^* > fph^{opt}$.

The consumer's choice of h_t^* in each period is a function of the total price of one kWh of heating, $[p_t(fph) + epf(fph) \cdot \tau_t] \cdot fph$, from the first-order condition $U'(h_t^*) = [p_t(fph) + epf(fph) \cdot \tau_t] \cdot fph$. Since $U'' < 0$, $dh_t^*/dfph < 0$. When $fph = fph^{opt}$, $h_t^* = h_t^{opt}$. But when $\beta < 1$, $fph^* > fph^{opt}$, so $h_t^* < h_t^{opt}$ for each period t¿0 (and vice versa).

C.2.3. Proof 3:

Proposition:
Let $\beta < 1$: The first best is achieved by setting $\tau_t = \tau_{pig}$ in each period $t > 0$ and setting a technology subsidy in the form of $(\frac{1}{fph_{min} - fph_{max}} \cdot fph + \frac{1}{1 - \frac{fph_{min}}{fph_{max}}}) \cdot \sigma$ with $\sigma = (fph_{min} - fph_{max}) \cdot (\beta - 1)$
$\cdot \sum_{t=1}^{T} \delta^t \cdot h_t^{opt} \cdot \big[[p_t(fph^{opt}) + epf(fph^{opt}) \cdot \tau_t^{pig}] + [p_t'(fph^{opt}) + epf'(fph^{opt}) \cdot \tau_t^{pig}] \cdot fph^{opt} \big]$.
Proof:
The subsidy is defined as a monetary benefit σ that is scaled with $\frac{1}{fph_{min} - fph_{max}} \cdot$

$fph + \frac{1}{1-\frac{fph_{min}}{fph_{max}}}$. The consumer's problem is:

$$\begin{aligned} \max_{fph,\{h_t\}_{t=1}^{T}} \quad & -c(fph) + (\frac{1}{fph_{min} - fph_{max}} \cdot fph + \frac{1}{1-\frac{fph_{min}}{fph_{max}}}) \cdot \sigma \\ & + \beta \cdot \left[\sum_{t=1}^{T} \delta^t \cdot \Big[U(h_t) - [p_t(fph) + epf(fph) \cdot \tau_t^{pig}] \cdot fph \cdot h_t \Big] \right] \end{aligned} \tag{C.4}$$

Subject to

$$U'(h_t) - [p_t(fph) + epf(fph) \cdot \tau_t^{pig}] \cdot fph = 0, \forall t \tag{C.5}$$

Consider this problem's Lagrangian, where the constraint from the period t choice of h_t^* has a multiplier λ_t. The first-order condition with respect to h_t is:

$$\beta \cdot \delta^t \Big[U'(h_t^*) - [p_t(fph^*) + epf(fph^*) \cdot \tau_t^{pig}] \cdot fph^* \Big] + \lambda_t \cdot U''(h_t^*) = 0 \tag{C.6}$$

The term in brackets is zero from the first-order condition from the static choice of h_t, Since U" is strictly negative, $\lambda_t = 0$ for all $t > 0$. Then, the first-order condition for fph is:

$$\begin{aligned} & - c'(fph^*) \\ & + \frac{1}{fph_{min} - fph_{max}} \cdot \sigma \\ & - \beta \cdot \Big[\sum_{t=1}^{T} \delta^t \cdot h_t^* \cdot \Big[\quad [p_t(fph^*) + epf(fph^*) \cdot \tau_t^{pig}] \\ & \qquad\qquad + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t^{pig}] \cdot fph^* \Big] \Big] \\ & = 0 \end{aligned} \tag{C.7}$$

With the value of σ as given, this first-order condition can be written as:

$$\begin{aligned} & - c'(fph^*) \\ & - \sum_{t=1}^{T} \delta^t \cdot \Bigg[\beta \cdot h_t^* \cdot \Big[\quad [p_t(fph^*) + epf(fph^*) \cdot \tau_t^{pig}] \\ & \qquad\qquad + [p_t'(fph^*) + epf'(fph^*) \cdot \tau_t^{pig}] \cdot fph^* \Big] \\ & + (1-\beta) \cdot h_t^{opt} \cdot \Big[\quad [p_t(fph^{opt}) + epf(fph^{opt}) \cdot \tau_t^{pig}] \\ & \qquad\qquad + [p_t'(fph^{opt}) + epf'(fph^{opt}) \cdot \tau_t^{pig}] \cdot fph^{opt} \Big] \Bigg] \\ & = 0 \end{aligned} \tag{C.8}$$

When $fph^* = fph^{opt}$, then $h_t^* = h_t^{opt}$ for all $t > 0$ since $\tau_t = \tau_t^{pig}$. Plugging $fph^* = fph^{opt}$ and $h_t^* = h_t^{opt}$ in Equation C.8 makes it equal to the social planner's first-order condition. So fph^{opt} and h_t^{opt} solve the consumer's problem, and by the second-order condition this is a unique solution.

C.3. Numerical simulation

C.3.1. Household's heating valuation

Mertesacker (2021) provides a utility function and estimates of its parameters for a case study on energy consumers in Germany. The utility function from Equation (4.11) includes a household's indoor temperature valuation factor γ. γ is obtained by multiplying household characteristics x as binary vector and the estimated coefficient for each characteristic δ. We specify the utility function for the case study by defining an example household by its characteristics x and corresponding estimated marginal utility of indoor temperature δ. The characteristics and estimates of the corresponding marginal utility from indoor temperature stem from Mertesacker (2021) as listed in Table C.1. For the case study in this paper, we construct three sample households covering the potential spread of valuations as shown in Table C.1. The base household has a valuation of 25€ $/\Delta T^2$, while the minimum obtained value is 13€ $/\Delta T^2$ and the maximum 38€ $/\Delta T^2$. For simplicity, we utilize valuations of 15€ $/\Delta T^2$, 25€ $/\Delta T^2$, and 35€ $/\Delta T^2$ in the valuation sensitivity.

C.3.2. Building's heat demand

The heat demand for the representative building used in the numerical case study is based on the building "SFH 1" from the building stock model of Diefenbach et al. (2015) and IWU (2016)[36]. The building definition in Diefenbach et al. (2015) is part of a model for the German building stock of the year 2009 via six representative average buildings. In this model "SFH 1" represents the most common average building in Germany. It is a single-family home with 147.1 m^2 of floor area. Based on the calculations implemented in IWU (2016), the specific heat demand of the household (including domestic water supply, storage, and distribution losses) for the ideal room temperature of 21°C is set to 224 kWh/m^2. This value includes an assumed reduction factor of 0.86 which corrects for the heated area and the reduction of temperatures during the night. Using the calculation methods and definitions from IWU (2016), the heat demand is determined for different temperature levels.

[36] Specified with the code DE.National.2009.002.01

Table C.1.: Estimates of a household's characteristic's effect on marginal utility from indoor temperature from Mertesacker (2021).

Parameter		δ Coefficent	Base	x Min	Max
Constant		12,256	1	1	1
Age	30-39	1.262	0	0	0
	40-49	0.094	1	1	0
	50-59	3.918	0	0	0
	≥ 60	4.811	0	0	1
# adults	2	3.014	1	1	0
	3	6.654	0	0	1
	≥ 4	3.850	0	0	0
# children	1	-0.368	0	1	0
	≥ 2	2.964	1	0	1
Is employed		-2.234	1	1	0
Has Abitur		3.271	1	0	1
Is owner		-0.033	1	1	0
Income	< 1,500€	2.329	0	0	1
	$\geq$ 3,500 €	0.320	0	1	0
Dwelling size	Small: < 1st tercile	-1.103	0	1	0
	Large: > 2nd tercile	5.322	1	0	1
Valuation βx in € $/\Delta T^2$			25	13	38

C.3.3. Heating technologies

Within the case study, we utilize stylized continuous functions of investment costs, CO_2 emissions, and fuel prices depending on the chosen fph-level. These functions are based on technical and economic heating system parameters from Danish Energy Agency (2021), emission intensities from BAFA (2021), and fuel price trajectories from Pickert et al. (2022). Danish Energy Agency (2021) provides data on real heating systems, including reference capacities, efficiencies, and cost components, as shown in Table C.2. We combine the solar thermal system with both an oil boiler and a gas boiler to obtain in total five investment options for the household in the case study. fph is the reciprocal of the efficiency. The efficiency of the combined heating system of a boiler and solar thermal results from the assumption that the solar thermal accounts for 20% of heat demand (BDEW, 2020). The investment costs of for each technology are obtained by scaling the equipment costs from Table C.2 to the uniform heating system size of 12.5 kW for the conventional technologies and 6.25 kW for the heat pump and adding the corresponding installation costs. Figure C.2 illustrates the resulting investment costs depending on fph, both for the discrete heating systems and a fitted exponential function.

The fuel data in Table C.3 contains the CO_2-intensites from BAFA (2021) and the average fuel prices over the next 20 years from Pickert et al. (2022). Note that the fuel prices are final consumption prices accounting for grid fees and other levies. Accounting for the efficiencies of the heating systems, Figure C.2 shows the resulting discrete emission intensities and fuel prices in dependence of fph as well as fitted linear functions.

Table C.2.: Technical and economic properties of oil boiler, gas boiler, air-to-water heat pump, and solar thermal systems (Danish Energy Agency, 2021).

Heating technology	Capacity	Efficiency	Equipment costs	Installation costs
	kW_{th}		€	€
Oil boiler	20	0.92	4260	1300
Gas boiler	14	0.98	2702	1158
Air-to-Water heatpump	7	3.15	6780	3830
Solar thermal	4.2		2872	1228

Table C.3.: Energy prices based on Pickert et al. (2022) and CO_2-intensities based on BAFA (2021).

Fuel	Fuel price €/kWh	CO_2-intensity $kgCO_2$/kWh
Oil	0.0738	0.266
Gas	0.0743	0.201
Electricity	0.3142	0

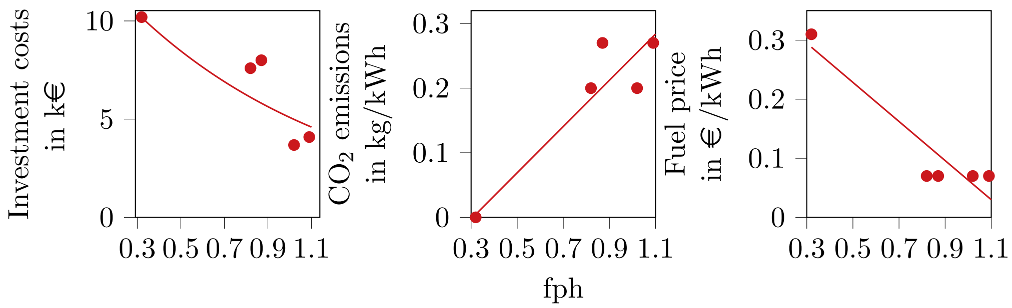

Figure C.2.: Investment costs, CO_2 emissions, and fuel prices for different heating technologies, including gas and oil condensing boiler, gas and oil boiler combined with a solar thermal system, and an air-source heat pump. Both the discrete technologies as well as fitted functions are displayed.

D. Supplementary Material for Chapter 5

D.1. Data

Table D.1 lists the main variables used in the analysis. The shown characteristics include the symbol, mean, minimum, maximum, standard deviation, unit, and source. Final energy consumption per capita is detailed for total energy, as well as broken down by industry, transport, and residential sectors, showing significant variability within and across sectors. Electricity consumption per capita follows a similar structure, highlighting the differences in consumption patterns among sectors. The table also includes the share of ICT capital at both the aggregate and sectoral levels, which serves as a proxy for digitalization. Additionally, economic activity is captured through GDP per capita, industrial production index, and private consumption per capita, providing a backdrop against which the energy consumption and digitalization data can be contextualized. The Economic Complexity Index (ECI) and various efficiency indicators offer insights into the structural and operational aspects influencing energy use. Control variables such as oil price, heating degree days, the share of natural resources, patents per capita, and average school years are included to account for external factors that might affect the observed relationships.

Table D.1 shows that for energy consumption, the average per capita figures reveal substantial variations, with the total consumption averaging at 26.14 MWh, indicating significant energy use differences across the industry (6.737 MWh), transport (8.533 MWh), and residential (6.646 MWh) sectors. Electricity consumption per capita shows a similar pattern of variability, with the total average at 5.764 MWh. The industry sector's average stands at 2.180 MWh, highlighting its substantial electricity demand, while the transport sector has the lowest average at 0.104 MWh, reflecting its minimal reliance on electricity compared to other forms of energy. Residential electricity consumption averages at 1.629 MWh, underscoring the sector's considerable but varied electrical energy use.Moreover, the ICT capital share statistics show a total average share of 0.927%, with the industry sector leading at 3.627%, followed by transport at 1.847%, and a relatively lower share in the residential sector at 0.093%.

Figure D.1 illustrates the relationship between digitalization and energy consumption across the industry, transport, and residential sectors in the EU-28 from 2007 to 2020. It shows the average digitalization of the 27 countries as a line, along with the average energy and electricity consumption represented as bars. Within these bars, electricity consumption is distinguished in black, indicating its proportion of total consumption. Following the financial crisis, the industry sector experienced a marked decrease in both energy and electricity usage, which later stabilized. This trend suggests a possible correlation between ICT capital intensity and reduced energy consumption, partially influenced by the EU Emission Trading Scheme. Energy consumption in the transport sector declined until 2013, then increased, followed by a significant reduction during the COVID-19 pandemic due to decreased mobility; meanwhile, electricity use remained relatively low but gradually increased with the adoption of electric vehicles, predominantly supported by the existing rail system. The residential sector exhibited the smallest reduction in energy consumption, affected by weather conditions and showing stable yet slightly decreasing electricity usage, which indicates enduring consumption patterns and the longevity of capital assets. Despite advancements in digitalization, the trends in energy and electricity consumption across these sectors were varied, indicating reductions in the industry and residential sectors, while the transport sector showed fluctuating consumption patterns, reflecting shifts in efficiency and behavior.

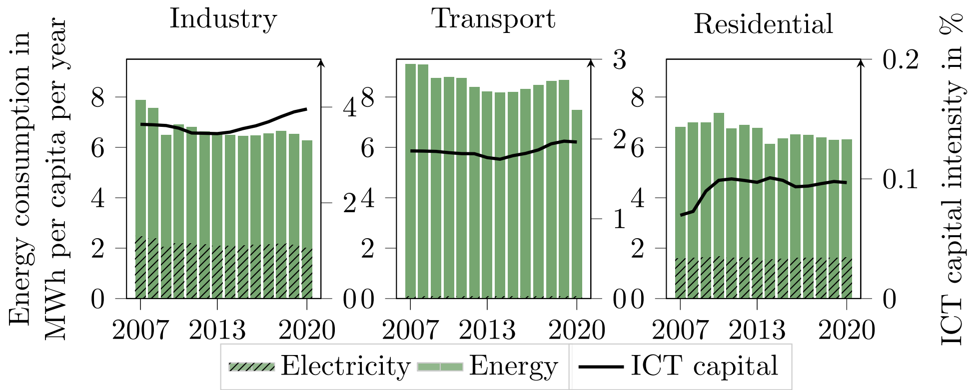

Figure D.1.: The development of energy and electricity consumption and ICT capital shares in the sectors industry, transport, and residential on average for the EU-28 between 2007 and 2020.

Table D.1.: Descriptive statistics of all variables

Variable	Symbol	Mean	Min.	Max.	St. Dev.	Unit	Source
Energy consumption pc							
Final energy							IEA (2023a)
Total		26.14	10.27	95.04	13.35	MWh	
Industry		6.737	1.114	26.26	4.485	MWh	
Transport		8.533	2.540	53.77	7.332	MWh	
Residential		6.646	1.816	12.60	2.285	MWh	
Electricity							IEA (2023a)
Total		5.764	1.846	16.28	2.906	MWh	
Industry		2.180	0.387	8.842	1.605	MWh	
Transport		0.104	0	0.419	0.085	MWh	
Residential		1.629	0.497	4.903	0.820	MWh	
Digitalization							
ICT capital share							Stehrer and Sabouniha (2023)
Total		0.927	0.510	0.188	2.831	%	
Industry		3.627	2.213	0.505	13.10	%	
Transport		1.847	0.801	0.266	3.998	%	
Residential		0.093	0.0941	0.011	0.584	%	
Economic Activity pc							
Gross domestic product	GDP pc	30.62	5.964	105.5	20.10	k$\$_{2015}$	World Bank (2023b)
Private consumption		14.01	7.209	24.43	3.649	k€	Enerdata (2023b)
Structure							
Economic complexity index	ECI	1.200	0.018	2.329	0.515	Index	GLaHU (2019)
Efficiency							
Gross efficiency index							Enerdata (2023b)
Industry		22.63	16.71	-18	68	Index_{2000}	
Transport		2.87	12.52	-39	33	Index_{2000}	
Residential		18.97	10.94	-8	46.28	Index_{2000}	
Control variables							
Energy price index		101.1	7.613	77.36	120.6	Index_{2015}	IEA (2022)
Heating degree days	HDD	2,782	322.4	6,180	1,129	d	Enerdata (2023b)
Patents per capita	Patents	885.2	31.26	5,969	1,067	Number	WIPO (2023)
Average school years	School	11.86	7.672	14.13	1.211	y	UNDP (2022)
Share of free allowances	Free allowances	74.28	25.17	24.98	1.080	%	EEA (2024)

D.2. Flow and stock variables of digitalization

In our analyses, we use the ICT capital share in total capital as a measure of digitalization. Unlike flow variables such as energy consumption or economic activity, a stock measure may underestimate ICT's role, as it captures capital accumulation rather than utilization. Given that ICT applications and usage have grown in recent years, the stock variable likely understates ICT's effect on energy consumption. For comparison, we also consider two alternative measures of digitalization: ICT capital compensation (a flow variable) and a societal digital index capturing broader technological trends.

To capture the economic impact of digitalization as a flow, we follow the literature (Schulte et al., 2016, Taneja and Mandys, 2022) and compute ICT capital compensation. Since ICT capital compensation is not directly available in the EU KLEMS database (Stehrer and Sabouniha, 2023), we derive it using the the growth accounting framework. The income share of ICT capital is obtained by dividing ICT's contribution to value added growth ($VACOn$) by the growth rate of ICT capital services, measured as the year-on-year change in the quantity index ($CAPICT\_QI$). Multiplying the income share by total capital compensation ($COMP$) yields ICT capital compensation in monetary terms, specified in equation (D.1). For the residential sector, we use private expenditures on ICT goods and services (eurostat, 2025, ONS, 2025), as detailed in D.3. The aggregated digitalization index is then constructed as first principal component of the three sectors industry, transport, and residential.

$$COMP_{t,j}^{ICT} = COMP_{t,j} \frac{VACOnTAngICT_{t,j} + VACon\_Soft\_DB_{t,j}}{CAPICT\_QI_{j,t} - CAPICT\_QI_{j,t-1}} \tag{D.1}$$

The Digital Economy and Society Index (DESI) is constructed by the European Commission to capture differences in digital maturity across EU-28 countries (EU, 2023). In high-income environments such as the EU, where single-technology penetration often approaches saturation, DESI's broad scope makes it a suitable measure. It covers four dimensions: connectivity, human capital, integration of digital services, and digital public services. The first three correspond to common components of digitalization indices: digital technical capital (infrastructure and tools enabling digital activities), digital human capital (skills for effective digital technologies) and digital technology use (technology integration across various sectors) (ITU, 2022, Portulans Institute, 2022, Shahbaz et al., 2017).

Table D.2.: The effect of digitalization, measured by digital capital compensation and the digitalization index DESI, on aggregate energy and electricity consumption using the system GMM estimator.

Variable	Energy		Electricity	
	(1)	(2)	(3)	(4)
	Compensation	DESI	Compensation	DESI
L.dep	0.814***	0.696***	0.821***	0.774***
	(0.05)	(0.08)	(0.07)	(0.07)
Digitalization	-0.014***	-0.299***	-0.004**	-0.166**
	(0.00)	(0.11)	(0.00)	(0.08)
Economic activity	0.104***	0.154***	0.096**	0.124***
	(0.03)	(0.03)	(0.05)	(0.05)
Energy price	-0.312***	-0.288***	-0.194***	-0.176***
	(0.04)	(0.04)	(0.05)	(0.05)
HDD	0.083***	0.132***	0.040**	0.051**
	(0.02)	(0.03)	(0.02)	(0.02)
Fin. crisis	-0.069***	-0.067***	-0.072***	-0.072***
	(0.01)	(0.01)	(0.01)	(0.01)
COVID	-0.087***	-0.050***	-0.061***	-0.040***
	(0.01)	(0.02)	(0.01)	(0.01)
Constant	-0.075	-0.167	-0.117	-0.186
	(0.11)	(0.15)	(0.17)	(0.22)
AR(2)	0.453	0.583	0.120	0.154
Hansen test	24.91	23.67	21.92	20.14
P-value	0.205	0.311	0.257	0.449
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests.

D.3. Digitalization variables in the residential sector

Analogous to the industry and transport sectors, digitalization in the residential sector is approximated by the NACE Rev. 2 category *Real Estate Activities* (eurostat, 2008). The sector includes "...operating of self-owned or leased [...] apartment buildings and dwellings" and "... provision of homes and [...] flats or apartments for permanent use", thereby capturing fixed installed assets such as smart home systems. The main advantage of the NACE REv. 2 category as proxy is its consistency with the measures for industry and transport, both in interpretation and data source. It comes with two limitations because EU KLEMS reports data on the production side, while the residential sector is primarily consumption-oriented. First, the measure may reflect ICT used by real estate firms, introducing noise. Second, digitalization in households occurs through mobile smart devices (e.g., smartphones), which are not included in installed capital.

An alternative measure, though inconsistent with the main digitalization indicators, is private expenditures on ICT goods and services (eurostat, 2025, ONS, 2025). Table D.3 reports the residential sector estimates using private ICT expenditures. In both energy and electricity models, digitalization measured via private ICT expenditure exhibits higher significance than when using ICT capital in the real estate sector.

Table D.3.: The effect of digitalization, measured by private expenditures for ICT goods and services, on residential energy and electricity using the system GMM estimator.

Variable	Energy	Electricity
	(1)	(2)
L.dep	0.680***	0.933***
	(0.07)	(0.03)
Digitalization	-0.323**	-0.102**
	(0.15)	(0.04)
Economic activity	0.294***	0.080**
	(0.10)	(0.04)
Energy price	-0.100*	-0.028
	(0.06)	(0.05)
HDD	0.203***	0.012
	(0.04)	(0.01)
Fin. crisis	0.006	-0.002
	(0.01)	(0.01)
COVID	0.024**	0.015**
	(0.01)	(0.01)
Constant	-1.549***	-0.168
	(0.42)	(0.13)
AR(2)	0.774	0.993
Hansen test	26.75	22.71
P-value	0.142	0.303
Obs.	364	364
Countries	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests.

D.4. Two-step system GMM

Table D.4.: The effect of digitalization on disaggregate energy and electricity using the two-step system GMM estimator.

(a) Columns (1)-(4) for energy consumption.

Variable	Energy			
	(1)	(2)	(3)	(4)
	Industry	Industry	Transport	Residential
L.dep	0.752***	0.749***	0.756***	0.411***
	(0.08)	(0.07)	(0.07)	(0.09)
Digitalization	-0.061***	-0.054**	0.037	-0.272
	(0.02)	(0.03)	(0.02)	(0.26)
Economic activity	0.226**	0.213**	0.096**	0.318***
	(0.10)	(0.10)	(0.04)	(0.11)
Energy price	-0.212***	-0.292***	-0.376***	-0.153
	(0.07)	(0.07)	(0.07)	(0.10)
Free allowances		0.040*		
		(0.02)		
HDD	0.186***	0.180***	0.022	0.374***
	(0.06)	(0.05)	(0.01)	(0.08)
Financial crisis	-0.137***	-0.146***	-0.061***	-0.007
	(0.02)	(0.02)	(0.01)	(0.02)
COVID	-0.034**	-0.028*	-0.157***	0.003
	(0.01)	(0.02)	(0.01)	(0.01)
Constant	-1.327***	-1.188***	0.330**	-2.495***
	(0.47)	(0.45)	(0.13)	(0.61)
AR(2)	0.312	0.232	0.098	0.792
Hansen test	19.53	21.55	22.12	26.56
P-value	0.312	0.365	0.334	0.148
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector.

(b) Columns (5)-(7) for electricity consumption.

Variable	Electricity		
	(5)	(6)	(7)
	Industry	Transport	Residential
L.dep	0.784***	0.938***	0.846***
	(0.12)	(0.07)	(0.08)
Digitalization	-0.036***	-0.002	-0.060*
	(0.01)	(0.00)	(0.04)
Economic activity	0.103**	0.003	0.052**
	(0.05)	(0.00)	(0.03)
Energy price	-0.157**	-0.008	-0.014
	(0.07)	(0.01)	(0.05)
HDD	0.063**	0.004	0.020
	(0.03)	(0.00)	(0.02)
Financial crisis	-0.087***	-0.003*	-0.003
	(0.01)	(0.00)	(0.01)
COVID	-0.027***	-0.006***	0.011*
	(0.01)	(0.00)	(0.01)
Constant	-0.299	-0.021	-0.130
	(0.29)	(0.03)	(0.18)
AR(2)	0.914	0.058	0.889
Hansen test	18.50	22.40	17.56
P-value	0.555	0.319	0.351
Obs.	364	364	364
Countries	28	28	28

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The economic activity measures are the GDP per capita in industry and transport, and the private consumption in the residential sector.

D.5. Exergy

The analysis uses total final energy consumption as the dependent variable, which has some caveats. It does not account for differences in useful work delivered by energy carriers; for instance, electrification (e.g., replacing gasoline vehicles with electric vehicles) may reduce final energy consumption without reducing useful work. Brockway et al. (2024) provide data on final exergy consumption, which measures the useful work in energy consumption. Table D.5 shows the effect of digitalization—approximated by capital share, capital compensation, and DESI—on exergy consumption. The coefficients remain negative, but their magnitude decreases compared to the final energy consumption estimates: capital share from -0.074 to -0.048, compensation from -0.014 to -0.012, and DESI from -0.299 to -0.106 suggesting that using final energy consumption may overestimate digitalization's effect. Digital capital compensation is least affected by the dependent variable change and remains significant at the 1% level, indicating lower correlation with electrification.

Table D.5.: The effect of digitalization, measured by ICT capital share, private expenditures for ICT goods and services, and DESI, on final exergy consumption using the system GMM estimator.

Variable	Exergy			
	(1)	(2)	(3)	(4)
	Base	Capital share	Compensation	DESI
L.dep	0.873***	0.824***	0.871***	0.817***
	(0.05)	(0.08)	(0.05)	(0.08)
Digitalization		-0.048	-0.012***	-0.106
		(0.04)	(0.00)	(0.12)
Economic activity	0.074***	0.072***	0.065***	0.090***
	(0.02)	(0.02)	(0.02)	(0.03)
Energy price	-0.324***	-0.352***	-0.326***	-0.318***
	(0.04)	(0.05)	(0.04)	(0.04)
HDD	0.066***	0.089**	0.069***	0.089***
	(0.02)	(0.04)	(0.02)	(0.03)
Fin. crisis	-0.080***	-0.078***	-0.082***	-0.079***
	(0.01)	(0.01)	(0.01)	(0.01)
COVID	-0.085***	-0.080***	-0.087***	-0.072***
	(0.01)	(0.01)	(0.01)	(0.02)
Constant	-0.035	0.012	-0.027	-0.074
	(0.09)	(0.14)	(0.09)	(0.12)
AR(2)	0.669	0.594	0.421	0.490
Hansen test	18.78	21.67	23.05	23.24
P-value	0.224	0.358	0.286	0.277
Obs.	364	364	364	364
Countries	28	28	28	28

Note: Heteroscedasticity-consistent standard errors are in parentheses. Windmeijer (2005) finite sample correction for standard errors is employed. *** p<0.01, ** p<0.05, * p<0.1. The values reported for AR(2) are the p-values for the null hypothesis of the Arellano and Bond (1991) tests of second-order autocorrelation in the first differenced errors. The "P-value" is reported for Hansen tests.

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Curriculum Vitae

CURRICULUM VITAE

Philipp Theile

PERSONAL DATA

Date of Birth	20th May 1992
Place of Birth	Ochtrup
Nationality	German

RESEARCH INTERESTS

Demand-side dynamics in the energy transition.
Electricity market analysis.
Individual decision-making and its implications for electricity demand.

EDUCATION

since 04/2019	**Institute of Energy Economics (EWI)** and **Department of Economics, University of Cologne** Doctoral Candidate in Economics
08/2016 - 02/2019	**KTH Royal Institute of Technology, Stockholm, Sweden** Master of Science in Engineering Double degree program with RWTH Aachen University Mobility period at KTH from 08/2016 to 01/2018
10/2015 - 10/2018	**RWTH Aachen University** Master of Science in Business Administration and Engineering: Electrical Energy Technology
10/2011 - 09/2015	**Leibniz University Hannover** Bachelor of Science in Engineering and Business Administration
07/2011	**Städtisches Gymnasium, Ochtrup** Maturity/Abitur

WORKING EXPERIENCE

since 02/2019	**Institute of Energy Economics at the University of Cologne (EWI)** Research Associate
04/2018 - 09/2018	**GridX GmbH, Aachen** Master Thesis Student
02/2016 - 07/2016	**FGH GmbH, Aachen** Working Student
06/2015 - 09/2015	**MTU Maintenance GmbH, Hannover** Internship
02/2014 - 08/2014	**Institute for Drive Systems and Power Electronics, Leibniz University Hannover** Student Assistant
10/2012 - 08/2014	**Institute of Algebra, Number Theory, and Discrete Mathematics, Leibniz University Hannover** Student Assistant

LANGUAGES

German	Native	French	Intermediate
English	Proficient	Swedish	Basic

PUBLICATIONS

Articles in Peer-Reviewed Journals:

- Arnold, F., Ashour Novirdoust, A., Theile, P. (2025). Environmental Policy Instruments for Investments in Backstop Technologies Under Present Bias-An Application to the Building Sector. *Environmental and Resource Economics*, 88(4), 1039-1070.
- Schlund, D., Theile, P. (2022). Simultaneity of green energy and hydrogen production: Analysing the dispatch of a grid-connected electrolyser. *Energy Policy*, 166, 113008.
- Marijanovic, Z., Theile, P., Czock, B. H. (2022). Value of short-term heating system flexibility–A case study for residential heat pumps on the German intraday market. *Energy* 249, 123664.
- Theile, P., Kesnar, C., Czock, B. H., Moritz, M., Novirdoust, A. A., Coors, V., Wagner, J., Schroeter, B. (2022). There's no place like home–The impact of residential heterogeneity on bottom-up energy system modeling. *Energy and Buildings*, 254, 111591.

Working Papers:

- Theile, P. (2025). The Shape of U – On the Structure of Utility from Electric Vehicle Charging. *EWI Working Paper* No. 25/07.
- Arnold, F., Ashour Novirdoust, Amir., Theile, P. (2023). Environmental policy instruments for investments in backstop technologies under present bias – an application to the building sector. *EWI Working Paper* No. 23/05.
- Schlund, D., Theile, P. (2021). Simultaneity of green energy and hydrogen production: Analysing the dispatch of a grid-connected electrolyser. *EWI Working Paper* No. 21/10.

Further Publications:

- Sprenger, T., Dressler, M., Schrader, E., Theile, P. (2024). Potenzielle Wasserstoffbedarfe in Hessen und Rheinland-Pfalz. *Study on behalf of the Landesverband der Energie- und Wasserwirtschaft Hessen/Rheinland-Pfalz e. V. (LDEW).*
- Gierkink, M., Frings, C., Niesler, N., Theile, P. (2023). Auswirkungen des Gebäudeenergiegesetzes auf Wohngebäude. *Study on behalf of the Förderinitiative Wärmewende der Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Arnold, F., Künle, E., Namockel, N., Theile, P. (2021). Stromversorgungssicherheit – Facetten und Herausforderungen. Weltenergierat, Energie für Deutschland 2021, Fakten, Perspektiven und Positionen im globalen Kontext. *Study on behalf of Gesellschaft zur Förderung des Energiewirtschaftlichen Instituts an der Universität zu Köln e.V.*
- Schlund, D., Theile, P. (2021). Strombezugsoptionen für Power-to-Gas-Anlagen. *emw, 4/2021, pp.2-5*
- Wagner, C., Theile, P., Künle, E., Greve, M. (2020). Auswirkungen des Kohleausstiegs auf die Frequenzstabilität im Energieversorgungssystem. *et - Energiewirtschaftliche Tagesfragen, Vol. 70 (3), 2020. pp. 19-22.*
- Wagner, J., Gierkink, M., Theile, P. (2019). Impuls zur aktuellen klimapolitischen Debatte. *Study on behalf of the German Energy Agency.*
- Theile, P., Towle, A. L., Karnataki, K., Crosara, A., Paridari, K., Turk, G., Nordstrom, L. (2018). Day-ahead electricity consumption prediction of a population of households: analyzing different machine learning techniques based on real data from RTE in France. *In 2018 IEEE International SmartGridComm Conference (pp. 1-6). IEEE.*

PRESENTATIONS AND TALKS

- On charging behavior at public charging stations in Germany - a discrete choice analysis of revealed-preference data. *International Ruhr Energy Conference (INREC).* August 2024. Essen.
- Does information substitute or complement energy? - A mediation analysis of their relationship in European economies. *Jahrestagung des Vereins für Socialpolitik (VfS).* September 2022. Basel, Switzerland.
- The economic viability of grid-connected power-to-hydrogen conversion - quantifying short- and long-term determinants. *12te Internationale Energiewirtschaftstagung an der TU Wien.* September 2021. Wien, Austria (online).