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Abstract

The transition to electric vehicles (EVs) shifts the complementary market for passenger transport from oil to electricity. We develop and estimate a joint equilibrium model linking the German vehicle and electricity markets, emphasizing the timing of EV charging as generation costs and emissions vary intraday. A 10% EV stock raises wholesale electricity prices by about 2%, creating a sizable pecuniary externality. Time-varying tariffs shift charging to cheaper hours and spur adoption, only partially alleviating the aggregate price pressure. Time-varying tariffs sustain EV adoption when the electricity market faces higher demand or carbon costs.

Keywords: electric vehicles, electricity markets, charging, complementary markets
JEL codes: L5, L6, L9, Q4, Q5

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1 Introduction

The automobile sector is undergoing a rapid and profound transformation. Electric vehicles (EVs) now account for more than 20% of global sales (International Energy Agency, 2025). This shift moves the complementary market for passenger transport from globally traded oil to locally produced electricity. Unlike oil, electricity is generated and priced within regional markets that exhibit sharp intraday fluctuations. As transport electrifies, EV adoption and electricity pricing become interdependent: higher EV demand can raise electricity prices, which in turn alters the cost and attractiveness of EVs. We quantify this two-way feedback between vehicle demand and electricity supply within a unified equilibrium framework.

Quantifying this feedback requires a structural model that jointly determines equilibrium in both the vehicle and electricity markets. We develop and estimate such a model using data from Germany. The framework integrates three components: a dynamic charging cost–minimization problem, a discrete-choice model of vehicle demand and pricing, and an electricity market with optimal dispatch and wholesale pricing. The charging decision provides the equilibrium link between the two markets—determining vehicle operating costs on one side and the timing and magnitude of electricity demand on the other.

The model allows us to address four central questions. First, how does EV adoption affect electricity prices and emissions through its impact on demand and generation? Second, do rising electricity prices feed back to limit further EV adoption? Third, can time-varying electricity tariffs mitigate price pressure while sustaining adoption? Finally, how do these interactions evolve with broader changes in the electricity sector—such as renewable entry, carbon pricing, or growing demand from other sectors? While we implement the model for Germany, the framework provides a general blueprint for studying market equilibria in electrifying economies.

The joint equilibrium model makes three main contributions. First, it explicitly incorporates intraday vehicle use and charging behavior, linking driving patterns to the timing of electricity demand—a key determinant of generation costs and emissions that standard vehicle market models abstract from. Second, it captures how additional electricity demand from EVs can raise prices during periods of inelastic supply, generating a pecuniary externality on all electricity consumers. Third, it endogenizes EV adoption as a function of electricity prices, closing the feedback loop between the vehicle and electricity markets. This structure enables us to quantify how pricing regimes and market transitions jointly shape EV adoption, electricity prices, and emissions.

Germany provides a particularly informative setting to study these interactions. Battery electric vehicles (BEVs) now account for over 18% of new vehicle sales, and the electricity market exhibits pronounced intraday variation in generation costs. The average wholesale price is about €100/MWh, but hourly prices range from roughly €75 to €125/MWh—a fluctuation of two-thirds within a single day.[1] Despite this volatility, retail and public-charging tariffs remain flat throughout the day. Because the marginal generation technology shifts between wind, solar, gas, and coal, the cost and emissions intensity of EV charging depend critically on the timing of charging. As emphasized by Holland, Mansur, Muller and Yates (2016), charging during coal-intensive hours can make EVs more polluting than combustion vehicles.

We model the joint equilibrium between the vehicle and electricity markets by specifying a dynamic charging cost–minimization problem, a vehicle demand and pricing model, and an electricity market with optimal dispatch. The equilibrium is defined by the simultaneous clearing of the annual vehicle market and the hourly electricity market.

The charging cost–minimization problem takes exogenous individual driving profiles as input and determines the timing and cost of electricity consumption required to operate an EV. Individuals solve a finite-horizon dynamic discrete-choice problem in which charging decisions depend on anticipated driving needs over a finite horizon. The model is related to the framework for commercial battery operators in Butters, Dorsey and Gowrisankaran (2025), but it differs by focusing on private EV owners who only consume electricity: they cannot resell stored energy, and driving is the sole way to deplete the battery.

The solution to the charging cost problem yields, for each individual–vehicle–market combination, the minimum electricity expenditure from home and public charging. These operating costs enter the vehicle market equilibrium as determinants of EV utility. The model also generates intraday electricity load profiles from EVs, which feed into the electricity market equilibrium to determine prices and generation.

We use data from over 60,000 respondents in the 2017 Mobilität in Deutschland survey to construct individual driving profiles that capture exogenous driving demand, home status, and access to home charging. For every combination of driving profile, EV model available on the German market, and region, we compute more than 11 million optimal charging patterns.

In the automobile market, manufacturers compete in prices in a Nash–Bertrand game. On the demand side, we extend Berry, Levinsohn and Pakes (1995) by embedding the optimal charging outcomes from the cost-minimization problem into vehicle operating costs.[2] Heterogeneous consumers—characterized by their travel profiles and implied charging costs—choose

[1]By comparison, prices of oil-based fuels such as gasoline and diesel fluctuate by only 3–4% intraday and about 10% over a year.

[2]Similar in spirit to Jia Barwick, Li, Waxman, Wu and Xia (2024), who integrate optimal travel mode choices into a residential location model.

among differentiated vehicles.

We estimate the vehicle demand and supply model using German vehicle registration and attribute data from 2012–2021. The model carefully distinguishes the utility derived from EVs and internal combustion engine (ICE) vehicles. EVs differ from ICEs because they depend on charging networks, battery capacity, and distinct driving characteristics. Moreover, the demand specification allows for heterogeneous disutility from operating costs—gasoline and diesel refueling, home charging, and public charging. This extends the literature on consumers' valuation of operating costs (e.g., Grigolon, Reynaert and Verboven, 2018; Bushnell, Muehlegger and Rapson, 2022) by differentiating between ICEs, EVs with home-charging access, and EVs without it.

The estimation accounts for endogenous vehicle prices and indirect network effects between charging stations and vehicle demand, following Springel (2021). Beyond standard aggregate market-share moments, we incorporate additional micro moments matching observed electricity demand at public charging stations and fuel-specific mileage patterns. Station-level data record hourly electricity consumption by region, showing that public charging typically begins around 7 a.m. and remains steady through the day, with rapid growth after 2016 as the EV stock expanded. Matching these moments is crucial to identify which drivers charge at home and to estimate the disutility from home and public charging. The mileage moments further identify whether high- or low-mileage drivers self-select into EV ownership.

Finally, we model the electricity market. The vehicle demand model provides individual choice probabilities linked to optimal charging profiles. Aggregating these probabilities yields the intraday electricity load curve from EV charging. We represent electricity supply through a merit-order model calibrated to the German market, assuming non-vehicle demand to be fixed and inelastic. While the framework abstracts from trading, transmission congestion, and ramp-up costs, it captures the key dynamics of price formation: the correlation between simulated and observed hourly wholesale prices in 2023 is 0.72.

The model allows us to study how the two markets jointly adjust as vehicle prices and electricity prices iterate to a fixed point where both the annual vehicle market and the hourly electricity market clear. Our first set of results examines the feedback loop between these markets under Germany's current flat-rate scheme and a counterfactual with time-varying electricity prices.

When EV chargers face fixed retail prices, they have no incentive to shift charging to off-peak hours, leading to inefficient load patterns and higher equilibrium costs (Joskow and Wolfram, 2012). Recent studies and pilot programs propose exposing consumers to time-varying prices to reallocate charging to low-cost hours (e.g., Bailey, Brown, Myers, Shaffer and Wolak, 2024). We extend this insight to the general equilibrium setting by quantifying how such reallocation affects electricity prices, generation costs, and EV adoption. Several governments and utilities are already experimenting with time-of-use or time-varying pricing for EVs.[3]

We evaluate the joint equilibrium starting from a market configuration expected to emerge within the next five years, in which electric vehicles represent 10% of the vehicle fleet—about 4.8 million cars.[4] At the end of 2024, Germany's EV stock stood at 1.65 million, and the government targets 15 million by 2030, making our baseline a plausible short-run scenario.

Under fixed electricity prices, a 10% EV stock raises wholesale prices by about 2.4%, yet this increase has almost no effect on EV adoption. The reason is straightforward: the operating cost advantage of EVs over internal combustion vehicles remains large, so modest electricity price increases do little to offset it. Consequently, large-scale adoption is likely to continue as EVs become more competitive. The higher electricity prices generate a substantial pecuniary externality—€1.7 billion in charging expenditures by EV owners induces an additional €1.1 billion in costs for other electricity users.

Introducing time-varying pricing initially reduces generation costs and charging expenditures by shifting demand to cheaper hours. However, the resulting decline in charging costs strengthens EV adoption, which raises overall electricity demand and pushes prices back up. In equilibrium, both average electricity prices and the pecuniary externality remain large—lower costs per vehicle are offset by higher aggregate adoption.

The emission savings from EVs are modest because the German electricity mix remains carbon-intensive, relying heavily on coal and gas. We estimate that EVs emit just over 90 gCO_2/km—barely below the current emission standard for new combustion vehicles. Interestingly, time-varying prices increase short-run emissions relative to fixed prices, as EVs tend to charge during off-peak hours when coal is frequently the marginal generation source.

However, this pattern is likely temporary. Time-varying pricing roughly doubles the profit gains of renewable generators relative to flat pricing, strengthening their incentives to enter and expand capacity. While current emissions are determined by the marginal (often fossil-fuel) supplier, future emissions depend on which technologies earn inframarginal rents today. Under time-varying rates, those rents accrue mainly to renewables; under flat prices, they accrue disproportionately to coal and gas.

[3]Bailey, Brown, Shaffer and Wolak (2025) evaluate a large-scale Canadian field experiment. Similar initiatives exist in the U.S.—for instance, TXU Energy offers free nighttime charging for Ford EV owners, and PG&E provides time-of-use rates for EVs.

[4]The demand model estimates a flow of annual vehicle sales. We scale the 2021 equilibrium flow of EV sales by a fixed factor to obtain an initial stock of 4.8 million EVs—roughly 10% of the vehicle fleet. This serves as the starting point of the simulation; the final equilibrium stock can deviate from this benchmark depending on the feedback between electricity prices and vehicle adoption.

Finally, we examine three factors shaping the ongoing energy transition: higher carbon prices, renewable expansion, and rising electricity demand from data centers and broader electrification. Increases in carbon prices or baseline electricity demand substantially reduce EV adoption when charging occurs at fixed rates, as higher wholesale prices directly raise operating costs. Time-varying pricing mitigates these effects by allowing EV owners to shift charging to cheaper hours, sustaining adoption even when the electricity market comes under pressure. Renewable expansion increases adoption only when prices vary over time, as time-varying pricing enables consumers to benefit from lower-cost renewable generation when it is abundant.

We contribute to a rapidly expanding literature on the transition to electric vehicles (EVs). One strand studies the determinants of EV adoption while taking electricity markets as exogenous. This work examines the role of charging infrastructure (Li, Tong, Xing and Zhou, 2017; Li, 2023; Springel, 2021; Fournel, 2025), purchase subsidies (Xing, Leard and Li, 2021; Muehlegger and Rapson, 2022), vehicle supply-side responses to subsidies (Armitage and Pinter, 2025; Jia Barwick, Kwon and Li, 2024; Remmy, 2025), and usage costs (Sinyashin, 2021; Bushnell, Muehlegger and Rapson, 2022; Dorsey, Langer and McRae, 2025). A second strand studies the impact of EV penetration on electricity markets, treating vehicle adoption as exogenous (Holland, Mansur, Muller and Yates, 2016; Holland, Mansur and Yates, 2022; Burlig, Bushnell, Rapson and Wolfram, 2021; Gillingham, Ovaere and Weber, 2024; Bailey, Brown, Myers, Shaffer and Wolak, 2024).

Our main contribution is to endogenize both sides of this relationship within a joint equilibrium framework that links vehicle demand, individual charging decisions, and electricity market outcomes. This allows us to quantify how EV adoption affects electricity prices and, in turn, how electricity pricing feeds back into EV adoption—an interaction overlooked when either market is modeled in isolation.

We make three further contributions to this literature. First, we develop a model that links EV adoption to the electricity market at a highly granular level. The framework generates endogenous intraday charging patterns and, as a result, endogenously varying electricity load curves. This structure allows us to conduct rich counterfactuals on how EV policies—such as time-varying tariffs or renewable expansion—affect load profiles, prices, and emissions.

Second, we micro-found individual battery charging and EV usage decisions. Modeling optimal charging behavior enables realistic substitution patterns between electric and conventional vehicles that depend on individual travel needs. This approach complements recent experimental work estimating charging elasticities, such as Bernard, Hackett, Metcalfe, Panzone and Schein (2025) and Metcalfe, Simpson, Schein and Sun (2025). The charging model and public charging data allow us to predict home-charging behavior that is otherwise unobservable, even in detailed electricity consumption data.

Third, we extend standard discrete-choice models of vehicle demand to incorporate separate disutilities from home and public charging. This distinction captures compatibility between vehicle attributes and infrastructure, yielding more realistic indirect network effects by recognizing that some drivers rarely or never rely on public charging.

We also contribute to the literature on complementary markets and their interactions. Examples include complementarities between hardware and software providers for compact discs (Gandal, Kende and Rob, 2000) and video games (Lee, 2013), between smartphone manufacturers and network operators (Chatterjee, Fan and Mohapatra, 2024), and between content providers and internet platforms (Jullien and Bouvard, 2022). In a related context, Benetton, Compiani and Morse (2023) analyze how rising electricity demand from crypto mining raises household and small-business electricity bills without considering feedback loops. Our paper extends this literature to the domain of large-scale electrification. We study how complementarities between the vehicle and electricity markets shape both environmental externalities and product-market outcomes. Methodologically, we show how individual usage decisions—here, battery charging behavior—micro-found the strength and direction of these cross-market interactions.

We proceed as follows. Section 2 describes the data and institutional setting. Section 3 presents the joint equilibrium model linking the vehicle and electricity markets. Section 4 discusses the estimation strategy and identification. Section 5 reports the estimation results. Section 6 then presents the simulation analysis and equilibrium counterfactuals.

2 Data

2.1 Data sources

We build a comprehensive data set combining sources on car registrations and usage, charging station entry and usage, and electricity generation and market outcomes in Germany between 2012 and 2023. These data jointly allow us to link EV adoption and charging behavior to electricity-market outcomes in a unified empirical framework.

Individual car-usage data. We use individual time use and travel records from the Mobilität in Deutschland 2017 survey. The data record each respondent's location status—at home, driving, or away from home—at one-minute intervals, which we aggregate to five-minute intervals. When driving, respondents also report the distance traveled. The survey further provides information on housing type (single-family home, two-family home, or apartment building), federal state, and the degree of urbanization of the respondent's county. The full sample contains 259,509 individuals in 136,357 households; after cleaning and restricting to drivers with complete daily records, we retain 60,414 individuals.

Vehicle registrations. We use zip-code–level registration data from the German Federal Motor Transport Authority (KBA), which record all new vehicle registrations by model and owner type each year. We treat these new registrations as sales. The analysis focuses on private owners and excludes corporate and fleet registrations,[5] We define a unique vehicle as the combination of manufacturer, model name, horsepower, engine size, and fuel type.

Vehicle prices and characteristics. We complement the registration data with information on list prices (treated as transaction prices) and vehicle attributes from the General German Automobile Club (ADAC). The ADAC data provide detailed characteristics, including fuel economy, size, vehicle class, and body type. For EVs, they additionally report battery capacity, energy efficiency, and driving range. We merge the ADAC and KBA datasets using our vehicle definition (manufacturer, model name, horsepower, engine size, and fuel type), yielding a panel of vehicle-level quantities, prices, and characteristics from 2012 to 2021.[6]

EV charging stations. We use data from the Federal Network Authority (Bundesnetzagentur) on all registered public charging stations in Germany. The dataset reports each station's location, opening date, charging speed, and number of charging points. From these records, we construct annual counts of public charging stations and charging points for every county in our sample, which we use to measure charging availability over time and space.

Charging data. We use transaction-level data on public EV charging from 2018–2021, covering all German states. These data, published by NOW GmbH and the National Centre for Charging Infrastructure, record every charging event at public stations that received entry subsidies, including the start and end times, duration, and electricity charged (kWh). For the state of Hamburg, we complement this information with more comprehensive data from Stromnetz Hamburg, which include nearly all charging events—irrespective of subsidy status—between 2016 and 2021. Together, these datasets provide detailed coverage of charging behavior across time and regions.

Mileage data. We use information on annual average mileage by fuel type from the insurance comparison and aggregation platform CHECK24.[7] The dataset reports average yearly driving distances for users of gasoline, diesel, and electric vehicles who signed insurance contracts through the platform in 2021. These data provide external information to estimate

[5] We do not model the incentives of firms to provide electric company cars or those of car-rental and taxi service providers since firm purchases are often driven by distinct tax and fleet-management considerations.

[6] We do not match on engine size for BEVs, as this characteristic is not defined for electric engines.

[7] `https://www.presseportal.de/pm/73164/5214728`, last accessed: October 22, 2025.

fuel-specific driving intensities.

Retail electricity and fuel price data. We use data from multiple sources to measure end-user energy prices. Information on retail electricity contracts that either include or are dedicated to BEV charging comes from the provider Enet, covering 2012–2021 with pricing details and contract availability by zip code. Yearly average public-charging rates for Germany are obtained from Verivox for the same period. Finally, we use average gasoline and diesel prices by county from 2012–2021, collected by Tankerkoenig, a data provider tracking fuel prices.

Electricity market data. We use hourly data from the Federal Network Agency (BNetzA) on wholesale electricity prices, renewable generation, and production units with a capacity above 10 MW in Germany. We complement these data with information on plant-level cost factors from the Institute of Energy Economics at the University of Cologne (EWI). Hourly system load data are obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E). The average EU ETS carbon price in 2023 comes from the German Environment Agency.[8] All electricity market data refer to the year 2023. We use 2023 as our reference year because the COVID-19 pandemic affected 2020 and 2021 and the Russia-Ukraine war 2022.

2.2 Descriptive Evidence

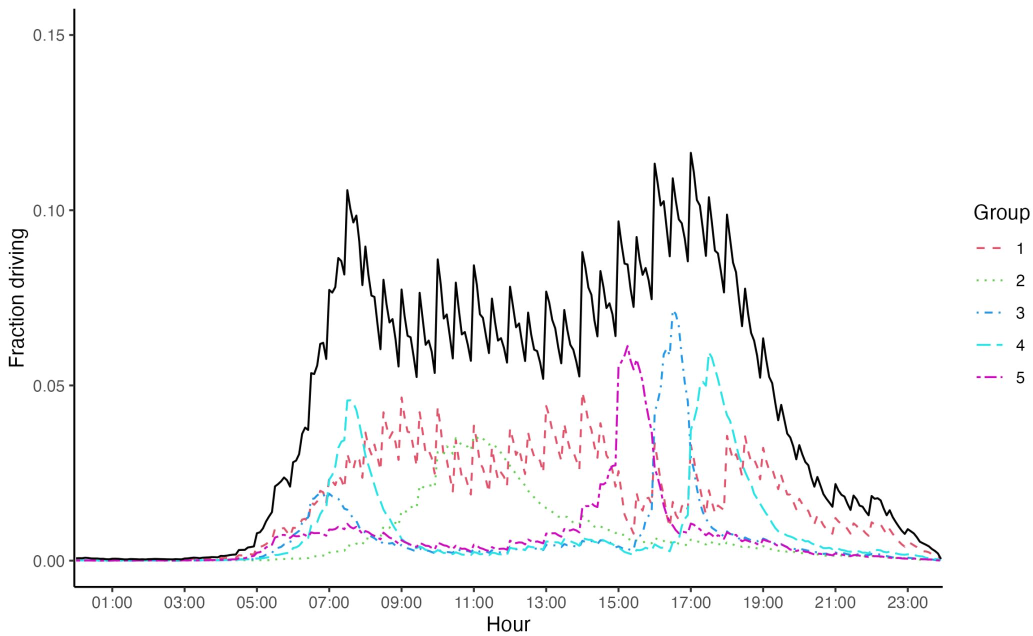
Use profiles The individual usage data provide rich variation in daily driving behavior. For illustration, we group individuals into five representative driver types using k-means clustering based on their travel patterns and distances traveled.

Figure 1 plots, for each driver group, the share of users on the road throughout the day; the black line aggregates these probabilities across all groups. The clusters capture typical usage patterns. Groups 2, 4, and 5 represent commuters leaving in the morning and returning in the afternoon or early evening. Group 3 mainly drives around midday, while Group 1 displays scattered driving throughout the day. Aggregating across all groups shows that almost all driving occurs between 7 a.m. and 7 p.m., with vehicles largely idle overnight.

The survey also records respondents' dwelling type, which we use to infer home-charging access — a key determinant of EV adoption. We assume that residents of single- or two-family homes can charge at home, whereas residents of larger apartment buildings cannot. Combining this with county-level urbanization data yields substantial geographic variation: about 32% of drivers in metropolitan areas report home-charging access, compared with 68% in urban counties and 74% in rural areas.

[8] `https://tinyurl.com/y3e2s6h9` , last accessed August 29, 2024.

Figure 1: Probability of driving throughout the day by driver group



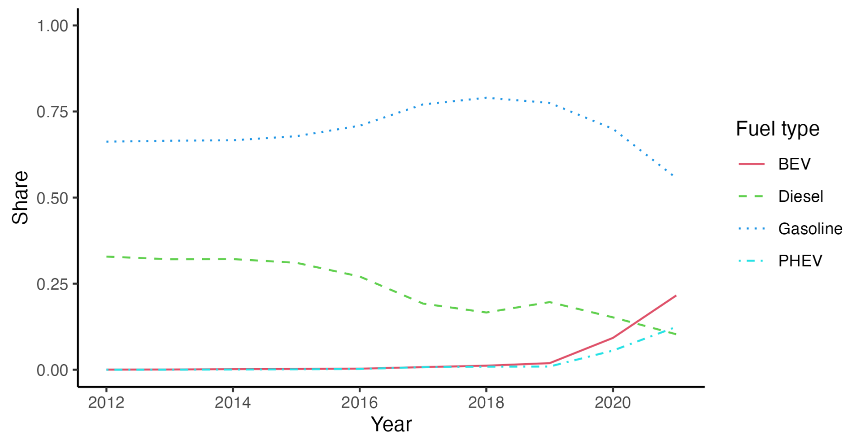
Note: The figure plots the probability of driving throughout the day for five groups obtained by k-means clustering on travel patterns and distances traveled. The groups contain 36,322, 6,136, 4,647, 7,125, and 6,184 individuals, respectively, for a total of 60,414. The black line aggregates across all groups. The saw-tooth pattern reflects discontinuities in reported time use.

The evolution of EV sales Figure 2 shows the evolution of vehicle sales by fuel type. As in most EU automobile markets, gasoline and diesel vehicles dominated German sales for decades. Beginning in 2016, alternative powertrains began to gain non-negligible market shares. By 2021, battery electric vehicles (BEVs)—vehicles powered solely by electricity—accounted for about 25% of new sales. Including plug-in hybrid electric vehicles (PHEVs), which combine a chargeable battery with a combustion engine, the combined market share approached 40%.

Our analysis focuses on BEVs, the fastest-growing segment and the only technology capable of fully decarbonizing the passenger fleet. We treat 2016 as the start of the EV market and disregard the small number of earlier BEV sales. We retain PHEVs in the data but treat them as gasoline or diesel vehicles, abstracting from the internal trade-off between charging and refueling. Empirical evidence from Grigolon, Park and Remmy (2024) shows that most PHEV users rely predominantly on combustion. We apply the same assumption to mild hybrids—combustion vehicles equipped with small, non–plug-in batteries.

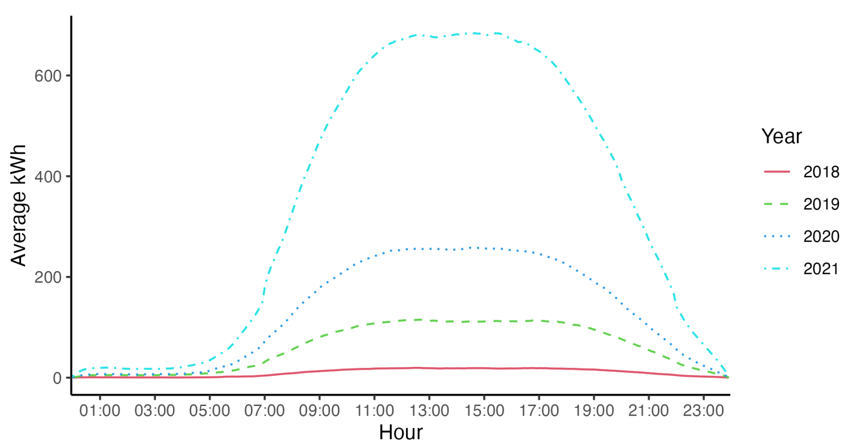
Charging Stations The expansion of public charging infrastructure closely followed the surge in EV sales. While many—mostly rural—counties had no public charging points in 2016, every county was equipped with at least some by 2021. By 2021, most counties hosted

Figure 2: Share of vehicle registrations by fuel type



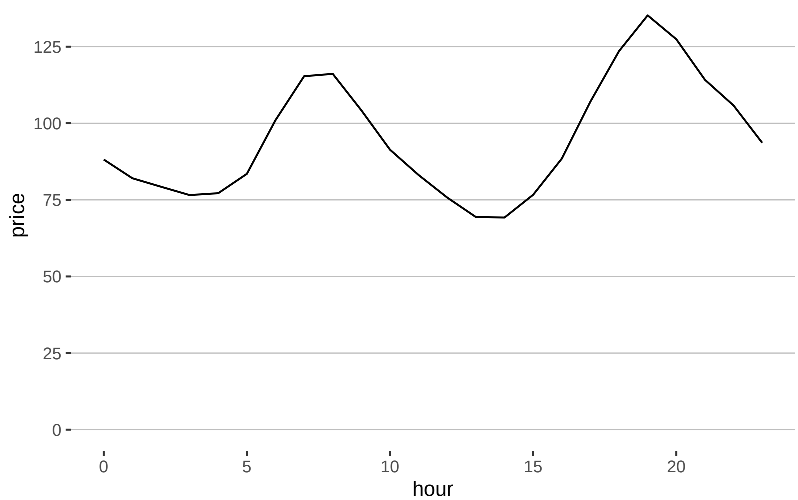
Note: The figure plots the share of new vehicle sales by fuel type—battery electric vehicles (BEV), diesel, gasoline, and plug-in hybrids (PHEV)—from 2012 to 2021.

Figure 3: Public charging throughout the day



Note: Note: The figure shows the average hourly electricity charged (kWh) during calendar years 2018–2021 at public stations that received entry subsidies.

Figure 4: Hourly wholesale prices throughout the day in EUR/MWh, 2023



Note: The figure plots the average hourly wholesale electricity price (EUR/MWh) for calendar year 2023.

between 2 and 5 public chargers per 10,000 inhabitants, with some exceeding 20.[9] Appendix Figure A1 maps the evolution of the number of public chargers per capita by county.

Public charging deployment was supported by investment subsidies: since 2007, Germany has offered grants of up to €8,000 for the installation and grid connection of Level-2 (≤22 kW) chargers, and larger subsidies for faster Level-3 chargers. Most chargers installed before 2021 are Level-2 units, which is why we assume Level-2 charging speeds in the empirical model. The largest operators of public charging stations are electricity producers, supermarkets, local utilities, and specialized start-ups. Nationally, the market is fragmented: in 2021, the ten largest firms operated only about 26% of all public charging points. At the regional level, however, concentration is substantially higher, and prices are consistently above residential electricity tariffs.

Figure 3 plots the evolution of mean daily electricity demand per station at charging stations that received investment subsidies. Public charging expanded sharply in parallel with BEV sales: between 2018 and 2021, average daily demand increased roughly 600-fold. Charging activity is concentrated in daytime hours, with almost no charging overnight, partly reflecting operators' common night-time restrictions. In the model, we therefore assume that public charging is unavailable overnight.

Intra-day wholesale electricity prices. Figure 4 plots the average hourly wholesale electricity price in Germany in 2023 throughout the day. Prices exhibit two pronounced

[9]Tesla's proprietary Supercharger network, restricted to Tesla owners during our sample period, is excluded from the count of public chargers.

peaks—around 8 a.m. and 6 p.m.—coinciding with high industrial and residential demand. Solar generation, which peaks midday, temporarily depresses prices between these two demand surges. The figure highlights the importance of charging timing: wholesale electricity prices vary by roughly 60% within a single day, implying that the electricity generation cost for EV charging depends critically on when vehicles connect to the grid.

3 Model

We introduce a joint equilibrium model of the new vehicle and electricity market. We specify vehicle demand and supply, electricity demand and supply, and how individual charging decisions create a complementarity between the markets. We first present the charging model, then describe the vehicle market, the electricity market, and the equilibrium. We model the importance of charging stations, but we do not allow them to respond strategically.

3.1 Notation and Timing

We consider a setting where consumers buy a vehicle with a lifetime T. The vehicle lifetime can be split into representative repetitive sequences running from $s = 1$ to S that capture the drivers' travel pattern. For example, with $T = 15$ years, we divide the lifetime into sequences of 14 days, each split into 1-hour intervals. We use the notation $(x_s)_{s=1}^{S}$ for sequences.

We define the new vehicle market as a combination of a calendar year t and a region g. A region is a state-county type combination, where the county type can be metropolitan, urban, mainly rural, or rural, as defined by the Federal Office for Building and Regional Planning.

The endogenous variables in the model are vehicle prices and electricity prices. Each calendar year t has J vehicles on sale, and their prices are p_j. Manufacturers set vehicle prices at the national level once per year. We use notation $\mathbf{p}$ to define the vector of all vehicle prices in a market. The electricity market clears in each period s of the sequence, and we define its geographical market as Germany as a whole. In each calendar year t, there are three energy price sequences: wholesale prices $(p_s^w)_{s=1}^{S}$, regional retail home-consumption prices $(p_{gs}^h)_{s=1}^{S}$, and public charging-station prices $(p_{gs}^a)_{s=1}^{S}$. Retail and charging prices vary across regions due to local markups. Our model jointly determines vehicle and electricity prices in equilibrium.

3.2 Charging Model

We model a dynamic finite-horizon cost minimization problem over the sequence S in which an individual chooses whether or not to charge their EV in each period s. The cost minimization is subject to electricity demand from driving needs and to battery capacity constraints. We treat individual driving needs derived from travel profiles as exogenous: consumers choose vehicles that accommodate their travel demand, not the other way around.

To obtain realistic charging patterns, we focus on a charging cost minimization problem with detailed intraday heterogeneity. The problem is defined for an individual travel profile w_i, a market gt, and a vehicle j. We describe each of these three determinants in turn.

Individual i has an intraday car travel profile $(w_{is})_{s=1}^{S}$, a sequence capturing location and travel information. Each w_{is} is a vector defining the travel profile of individual i at interval s: $(w_{is}) = (h_{is}, r_{is}, m_{is})$ where h_{is} indicates home status, r_{is} takes the value one if the individual is driving, and m_{is} denotes kilometers driven when $r_{is} = 1$. Together, these variables determine the location (home, on the road, away) and distance traveled over the sequence S.

The charging problem is market-specific because electricity prices vary across markets. We denote p^h_{sgt} as the home electricity price and p^a_{sgt} as the electricity price at charging stations.

The two relevant features of an electric vehicle j in the charging problem are battery size R_j in kWh and electricity consumption per kilometer e_j (kWh/km). The battery level B_s (in kWh) must satisfy

$$0 \leq B_s \leq R_j \quad \forall s \in \{1, \ldots, S\},$$

The charging speed C is the kWh added in an interval s, assumed constant.[10] Charging increases the battery level by $\min\{C, R_j - B_s\}$.

The charging problem is specific to each travel profile-vehicle-market combination. For exposition, we drop all but the period subscript s. In each interval s, an individual decides whether to charge the EV. This binary choice is denoted $c_s \in \{0, 1\}$. Charging affects next-period battery level according to:

$$B_{s+1} = \underbrace{\mathbb{1}\{r_s = 0\}(B_s + c_s \min\{C, R - B_s\})}_{\text{Charging or Idle}} + \underbrace{\mathbb{1}\{r_s = 1\}(B_s - m_s e)}_{\text{Driving}}$$
$$\forall s \in \{1, \ldots, S\}.$$

[10]The model could be extended with vehicle- and station-specific charging speeds to capture the role of fast charging.

If the travel profile indicates no driving in s, the individual may charge ($c_s = 1$) to raise the battery level by C (or $R - B_s$ if it is almost full), or not charge ($c_s = 0$) and keep the level unchanged. If instead w_s indicates driving, then there is no choice: the battery depletes by $m_s e$.

We present the cost minimization problem separately for individuals without home charging access, $l = 0$, and for individuals with home charging access, $l = 1$. For individuals without home charging, we have:

$$\begin{aligned} V_s^{l=0}(B_s) = \min_{c_s} & \left[\mathbb{1}\{r_s = 0\} c_s p_s^a \min\{C, R - B_s\} + V_{s+1}^{l=0}(B_{s+1}) \right], \\ & \text{s.t. } 0 \le B_s \le R \quad \forall s \in \{1, \ldots, S\} \end{aligned} \tag{1}$$

The program captures the idea that individuals are forward-looking: they consider future driving needs and electricity prices when deciding whether to charge. Whenever they are not driving, they can charge at a monetary cost of $p_s^a \times \min\{C, R - B_s\}$. For individuals with home charging, we have:

$$\begin{aligned} V_s^{l=1}(B_s) = \min_{c_s} & \Big[\mathbb{1}\{r_s = 0\} c_s (\mathbb{1}\{h_s = 1\} p_s^h + \mathbb{1}\{h_s = 0\} p_s^a) \min\{C,\, R - B_s\} \\ & \quad + V_{s+1}^{l=1}(B_{s+1}) \Big], \\ & \text{s.t. } 0 \le B_s \le R \quad \forall s \in \{1, \ldots, S\}. \end{aligned} \tag{2}$$

where h_s determines if i is at home or not. This program is similar to (1), however, these individuals can opt to charge at home at an electricity rate p_s^h.

The solution of the charging problem for each individual-vehicle-market combination gives cost-minimizing sequences of charging decisions $(c^*_{ijgts})_{s=1}^S$. The solution to the problem might not be unique, and in Section 4 we discuss how we select solutions. Some driving profiles are infeasible for certain EVs because they would violate the battery constraints. For such cases, we exclude the EV from the individual's choice set χ_i.

The solution enables us to construct electricity loads and expenses that enter both the vehicle and electricity market models. First, the optimal charging sequence gives rise to an electricity load sequence for each $ijgt$: $(e^*_{ijgts})_{s=1}^S$, which we split into home charging load $e^{h^*}_{ijgts}$ and station charging load $e^{a^*}_{ijgts}$. Aggregating the electricity load sequences over individuals and choice probabilities gives us the total electricity demand from EVs.

We also construct electricity expense variables to be used in the vehicle demand model. The variable $A^{l_i=0}_{ijgt} = \sum_{s=1}^S e^{a*}_{ijgts} p^a_{gts}$ defines the energy expenses for vehicle j when i cannot charge at home. Similarly, we define the expense for individuals with home charging as the expense at home, $H_{ijgt}^{l_i=1} = \sum_{s=1}^{S} e_{ijgts}^{h*} p_{gts}^{h}$, and the expense at charging stations $A_{ijgt}^{l_i=1} = \sum_{s=1}^{S} e_{ijgts}^{a*} p_{gts}^{a}$.

3.3 Vehicle Market

Vehicle Demand The exposition follows the BLP model Berry, Levinsohn and Pakes (1995) and extends Grigolon, Reynaert and Verboven (2018) to incorporate heterogeneity in expected fuel and electricity expenses. An individual i in market gt derives indirect utility from a car $j \in \chi_i$:

$$\begin{aligned} u_{ijgt} = & \sum_k x_{jgt}^k \beta_{ik} - \alpha_i p_{jt} + \xi_{jgt} + \epsilon_{ijgt} \\ & + \mathbb{1}\{EV_j = 0\}(C_{ijgt}^{ICE} \gamma^{ICE}) + \mathbb{1}\{EV_j = 1\}(C_{ijgt}^{EV} \gamma^{EV}). \end{aligned} \tag{3}$$

Here, x_{jgt} are observed attributes, ξ_{jgt} captures unobserved product-market attributes, and ϵ_{ijgt} is i.i.d. Type I extreme value distributed. Vehicle attributes include EV-specific variables such as range, the charging station density, and fuel-type fixed effects. The outside good utility is normalized to $u_{i0gt} = \epsilon_{i0gt}$.

We construct fuel costs C_{ijgt}^{ICE} for each driver profile w_i, based on average fuel prices, the fuel consumption, and the individual's distance traveled over the driving sequence S. The parameter γ^{ICE} measures the marginal disutility of one euro of fuel expense per S.

The EV electricity expense term in (3) is:

$$C_{ijgt}^{EV} \gamma^{EV} = \mathbb{1}\{l_i = 0\} \left[\gamma^a A_{ijgt}^{l_i=0}\right] + \mathbb{1}\{l_i = 1\} \left[\gamma^a A_{ijgt}^{l_i=1} + \gamma^h H_{ijgt}^{l_i=1}\right]. \tag{4}$$

Here, $\gamma^{EV} = (\gamma^a, \gamma^h)$ collects the marginal disutilities of station and home charging expenses. The first term captures expenses for individuals without home charging, while the second term captures both station and home expenses for individuals with home charging.

In total, three parameters capture the disutility from operating expenses: γ^{ICE} and $\gamma^{EV} = (\gamma^a, \gamma^h)$. Rational consumers might be expected to value vehicle price and one euro of the net present value of fuel or electricity costs equally. In this case, the γ^{ICE} and γ^{EV} can be interpreted as capitalization parameters that translate operating expenses over S into their net present value over the vehicle lifetime (which includes many sequences). However, a large body of literature shows that consumers undervalue future fuel costs relative to vehicle prices Hausman (1979); Busse, Knittel and Zettelmeyer (2013); Allcott and Wozny (2014); Grigolon, Reynaert and Verboven (2018). We follow this literature and estimate operating cost valuation but additionally allow the valuation of electricity costs to differ from that of fuel costs. Electricity prices may have lower salience, and refueling time and convenience costs may differ between oil fuels and electricity. Evidence supports this distinction: consumers do not value fuel and electricity expenses equally (Bushnell, Muehlegger and Rapson, 2022). Our specification further distinguishes between residential electricity expenses (γ^h) and charging-station expenses (γ^a), since consumers may experience greater disutility from charging at stations compared with simply plugging in at home, for instance due to the inconvenience of having to drive to a charging station or due to potential congestion at stations.

The EV-specific component of indirect utility has several important economic features. First, it allows us to examine the extent to which home and public charging differ in their effect on heterogeneous individuals' purchase decisions. We capture this through a micro-founded charging model that links individual travel profiles, EV attributes, and market conditions, including electricity prices. This extends the existing EV literature, which often specifies the indirect utility as a function of EV attributes without distinguishing between home and away charging or linking EV attributes to the battery charging problem (e.g., Springel, 2021; Remmy, 2025).

We derive individual choice probabilities $\sigma_{ijgt}(\mathbf{p}, (p^a_{gs})^S_{s=1}, (p^h_{gs})^S_{s=1}, (w_{is})^S_{s=1}, \nu_i)$ from the Type I Extreme Value assumption on ϵ and aggregate to model vehicle sales q_{jgt}:

$$q_{jgt} = \int\int L_{gt}\sigma_{ijgt}\big(\mathbf{p}, (p^a_{gs})^S_{s=1}, (p^h_{gs})^S_{s=1}, (w_{is})^S_{s=1}, \nu_i\big)\ dF_\nu(\nu_i)dF^g_{w_i}(w_i), \tag{5}$$

where $\sigma_{ijgt} = 0$ if $j \notin \chi_i$ and L_{gt} is the potential market size.[11] The random variable ν_i represents unobserved heterogeneity. The expression integrates over individual choice sets χ_i and the regional-specific distribution of travel profiles w_i. Vehicle demand depends on the three endogenous prices: vehicle prices p_j, residential electricity prices $(p^h_{gs})^S_{s=1}$, and charging station prices $(p^a_{gs})^S_{s=1}$. The electricity price sequences determine the expense terms in (4), obtained from the cost minimization problem.

Vehicle Supply Let J_f denote the set of vehicles produced by manufacturer f. Most

[11] The survey records drivers' reported trips and mileages, where each type has a share z_i among vehicle owners. These are fractions conditional on purchasing a vehicle, while the integral in equation (5) is defined over the entire population. Following Grigolon, Reynaert and Verboven (2018), we transform the conditional fractions z_i into population shares π_i using:

$$\pi_i = z_i\left(\frac{Q}{L\sum_j \sigma_{ij}}\right),$$

where subscripts gt are omitted for clarity, $Q = \sum_j q_j$ denotes total market sales and L is potential market size. We apply this transformation when integrating over the distribution of travel types F^g_{wi}.

manufacturers produce ICE and EV engines. A firm's annual profits are:

$$\Pi_{ft}(\boldsymbol{p}) = \sum_{g} \sum_{j \in J_f} [p_{jt} + \lambda_{jt} - mc_{jt}] \, q_{jgt}(\boldsymbol{p}, (p_s^h)_{s=1}^S, (p_s^a)_{s=1}^S), \tag{6}$$

where mc_{jt} is the marginal cost of vehicle j in year t, q_{jgt} is annual sales quantity in region g, and $\boldsymbol{p}$ is the vector of J vehicle prices in year t. A vehicle j may qualify for a purchase subsidy λ_{jt} in year t. In that case, firms receive $p_{jt} + \lambda_{jt}$ per unit sold, while consumers pay p_{jt}, the sticker price net of the subsidy. List prices are observed to be constant across regions, and we assume the same for marginal costs.

Assuming Nash-Bertrand competition, we obtain the first-order condition for profits with respect to prices. Let Ω be the ownership matrix, where the element Ω_{jh} indicates whether the same firm sells products j and h. Let $D(\boldsymbol{p})$ be a matrix with elements $D_{jht} = -\sum_g \frac{\partial q_{hgt}(\boldsymbol{p}, (p^h)_{s=1}^S, (p^a)_{s=1}^S)}{\partial p_{jt}}$. Then, the first-order condition of the firms' maximization problem is:

$$\boldsymbol{p} + \boldsymbol{\lambda} - (\Omega \odot D(\boldsymbol{p}))^{-1} \boldsymbol{q} - \boldsymbol{mc} = 0, \tag{7}$$

where $\boldsymbol{q} = \sum_g q_{jgt}$ is the vector of vehicle quantities, and $\odot$ denotes the Hadamard (element-wise) product. Vehicle manufacturers adjust their prices in response to electricity prices, as these shift demand.

3.4 Electricity market model

Electricity demand We assume that the electricity market is characterized by an inelastic base load E_{ts}^B, which represents electricity demand absent EV consumption. Total electricity demand in interval s is the sum of the base load and the EV-induced demand:

$$E_{ts}^D = E_{ts}^B + E_{ts}^{EV}, \tag{8}$$

where E_{ts}^{EV} is the aggregate load from EV's calculated from vehicle demand and the optimal electricity load profiles. The equation holds for all s, so we obtain the sequence $(E_{ts}^D)_{s=1}^S$ that describes the demand profile over the horizon S. Shifts in vehicle prices, such as those induced by subsidies, alter electricity demand through their impact on market shares (5). Electricity prices affect EV demand both via market shares and via the charging solution.

Electricity supply. Generators u supply electricity and can produce an amount e_{uts} at marginal cost mc_{ut}. Renewable generation varies throughout the day with wind and solar conditions, while thermal generators such as coal or gas can operate at constant capacity. We order generators by increasing marginal cost, with $u = 1$ having the lowest and $u = U$

the highest marginal cost. This ordering yields the merit order curve, a step function that defines the optimal dispatch. We assume no network congestion so that all generation can be dispatched flexibly to any region g within the market, and we ignore ramp-up costs. Furthermore, we ignore imports, exports, and generator market power. Under optimal dispatch, the system operator assigns generation to the lowest-cost units until demand is met. All inframarginal plants supply at full capacity, while the marginal plant supplies the residual needed to balance demand.

We define E_{st}^U as the total energy dispatched from generator units. The wholesale equilibrium price is $p_{st}^w = mc_{u^*t}$ where u^* is the marginal unit such that $\sum_{u=1}^{u^*-1} e_{ust} < E_{st}^D$ and $\sum_{u=1}^{u^*} e_{ust} \geq E_{st}^D$. We assume retailers charge a fixed markup per region, which links the wholesale price to retail and charging-station prices. If retail and charging-station prices do not vary within S, we obtain $p_{gt}^a = \mu_g^a + \bar{p}_t^w$ and $p_{gt}^h = \mu_g^h + \bar{p}_t^w$, where $\bar{p}_t^w = \frac{\sum_{s=1}^S p_{st}^w E_{st}^U}{\sum_{s=1}^S E_{st}^U}$ is the average load-weighted wholesale price and μ_g^a, μ_g^h are region-specific markups capturing regional variation in market-power. When retail and charging prices vary within S, we obtain $p_{gts}^a = \mu_g^a + p_{ts}^w$ and $p_{gts}^h = \mu_g^h + p_{ts}^w$.

3.5 Equilibrium

The equilibrium of the vehicle and electricity market in year t consists of a vector of vehicle prices $\boldsymbol{p}$ and a sequence of wholesale electricity prices $(p_s^w)_{s=1}^S$ such that:

1. For each individual-vehicle-market combination, the electricity load sequence $(e_{ijgts}^*)_{s=1}^S$ is given by the solution to the battery cost-minimization problem in (1) or (2), which yields electricity expenses $A_{ijgt}^{l_i=0}, A_{ijgt}^{l_i=1}, H_{ijgt}^{l_i=1}$.

2. Vehicle demand follows equation (5), and firms set vehicle prices $\boldsymbol{p}$ according to the first-order conditions in (7). The resulting vehicle market equilibrium determines EV electricity load E_{st}^{EV}.

3. Electricity demand is given by (8), supply is determined by optimal dispatch, and the market clears in every period: $E_{st}^U = E_{st}^D$; yielding equilibrium prices $p_{gts}^w, p_{gts}^a, p_{gts}^h$.

To build intuition about the interaction between the vehicle and electricity markets, we consider how introducing EVs into consumers' choice sets affects both sides of the economy. At prevailing electricity prices—wholesale (p^w), residential (p^h), and public charging (p^a)—a subset of consumers adopts EVs: consumers with specific travel profiles $(w_{is})_{s=1}^S$ select EVs based on their implied operating costs. These EV owners solve their charging cost–minimization problems, generating heterogeneous intraday electricity load profiles. Appendix Figure A3 illustrates the resulting partial vehicle-market equilibrium before electricity price adjustments in black.

Aggregating across EV adopters yields the EV-specific load curve sequence $(E_{ts}^{EV})_{s=1}^{S}$. This additional demand raises total electricity consumption in each period from E_{ts}^{B} to $E_{ts}^{B} + E_{ts}^{EV}$. Higher demand increases wholesale prices p^w, which pass through to retail electricity rates—residential (p^h) and public charging (p^a). These higher prices feed back into consumers' charging costs, leading them to adjust both charging behavior and, potentially, vehicle choice. The resulting changes in electricity demand further affect prices. The full market equilibrium, depicted in red in Appendix Figure A3, captures this iterative feedback loop between the vehicle and electricity markets.

Our counterfactual analysis in Section 6 quantifies the equilibrium complementarity between the vehicle and electricity markets and evaluates the extent to which higher electricity prices curb EV adoption. We compare outcomes under alternative electricity pricing regimes, focusing on a shift from fixed-price contracts to time-varying tariffs. The analysis examines how EV adoption influences electricity costs, emissions, generation costs, and producer profits, and how these effects depend on the structure of electricity pricing.

4 Estimation

This section describes the estimation of the charging model, the vehicle demand model, and the electricity market model. The solution of the charging model links electric vehicle demand (via electricity expenses) to the electricity market (via intraday load curves).

4.1 Solution Method for the Charging Model

We solve the cost minimization problems described in (1) and (2) to obtain charging costs and intraday load curves for each individual-vehicle-region combination. We construct individual travel profiles $(w_{is})_{s=1}^{S}$ directly from the car usage survey data. We restrict the sample to weekdays of car owners. To solve the dynamic charging model, we generate a horizon of $S = 14$ days by repeating the observed daily travel profiles 14 times. For each individual, the survey identifies the geographical market g. For each EV j, we observe the battery size R_j and per-kilometer electricity consumption e_j from the car registration data. We assume a uniform charging speed of 11 kW, consistent with Level-2 chargers, which account for the vast majority of public chargers installed before 2021.

We use the data on residential and public charging retail electricity rates to construct average regional electricity rates p^h_{gt} and p^a_{gt} by year. Public charging is always more expensive than home charging. In Germany, retail contracts are flat-rate, and charging station prices do not vary across the day. Hence, the observed prices are not s-specific and do not vary intraday. Our counterfactuals introduce intraday electricity price variation.

When electricity rates are flat, we first compute expenses for each travel-vehicle-region combination. If an individual can home charge, we check whether the EV is compatible with the travel profile relying exclusively on home charging. Since home charging is strictly cheaper than station charging, costs equal the home electricity rate multiplied by the required energy to satisfy the driving profile.

If home charging alone is insufficient, we test if the profile can be satisfied by combining home and station charging when the driver is away from home but not driving. We impose a nighttime restriction, disallowing station charging between 11 p.m. and 6 a.m., as supported by the data. Stations prohibit overnight parking, and observed station usage is negligible at night, as shown in Figure 3. If the combined charging suffices, the EV is included in the individuals' choice set χ_i, with costs equal to the sum of home and station charging expenses. If both sources together are insufficient, the EV is excluded from the choice set. Energy-efficient EVs and models with larger batteries are more likely to belong to χ_i.

For individuals without home charging access, we repeat the same procedure but allow charging in every non-driving period outside of the nighttime restriction. The cost of station charging is taken as the electricity expense. If these charges cannot cover the driving needs, the EV is excluded from the choice set. Consumers unable to home charge thus face a choice set with fewer EVs, especially if they drive a lot.

The absence of intraday electricity price variation causes a multiplicity problem when solving the dynamic charging model. For a given EV, an individual is indifferent between two different charging profiles whenever they imply the same amount of home and away charging, since the associated costs are identical.[12]

To resolve the multiplicity problem, we assume home charging follows the behavioral evidence in Bailey, Brown, Myers, Shaffer and Wolak (2024). Individuals plug in upon returning home after their last trip of the day and charge continuously until fully recharged. Station charging remains randomly spread over the day as observed in Figure 3.[13]

In counterfactuals with s-specific electricity rates, multiplicity does not arise. We solve

[12] The alternative charging solutions yield equal costs but imply different intraday load curves. Therefore, selecting the solution profile matters for the electricity market but not for the vehicle market, which depends only on total expenditures.

[13] For example, suppose a driver arrives home at 6 p.m., leaves at 8 a.m. the next morning, and needs 20 kWh, which requires 2 hours of charging. Under the assumption of plug in at home the driver charges from 6 p.m. to 8 p.m.

the dynamic model by backward induction and obtain a unique charging profile $(c^*_{ijgts})_{s=1}^{S}$ that determines home and station expenses and uniquely pins down the intraday load profile.

From the charging solutions we derive $A^{l_i=0}_{ijgt}$, $A^{l_i=1}_{ijgt}$ and $H^{l_i=1}_{ijgt}$ and determine χ_i. This is computed for each individual-vehicle-region combination, yielding over eleven million electricity cost estimates for EVs.

For ICE vehicles, we construct the fuel costs, C^{ICE}_{ijgt}, by multiplying the fuel price with the fuel required to cover the kilometers traveled in each travel-vehicle combination. We use regional fuel prices to compute fuel costs.

4.2 Demand Estimation

We estimate the demand model using regional market shares and micro-moments that discipline the mapping between travel profiles and EV adoption

We face four challenges in the demand estimation. First, firms set car prices knowing unobserved product characteristics, creating price endogeneity. Second, charging station density d_{gt} depends on EV demand, generating a potential endogeneity problem through indirect network effects. Third, we must define moments that identify the parameter vectors γ^{ICE} and γ^{EV}, which enter the individual-specific component of indirect utility. Fourth, we must estimate which consumer types adopt EVs to link the vehicle demand model with the electricity market.

To address these challenges, we define three types of moments: aggregate market share moments $E[\xi_{jgt} z_{jgt}] = 0$ based on the instrument matrix z_{jgt}; a state-level 5-minute station charging moment $E[\eta_{Gts}] = 0$ matching the observed public charging demand; and mileage moments $E[\eta^{m,EV}_t] = 0$, $E[\eta^{m,gasoline}_t] = 0$, and $E[\eta^{m,diesel}_t] = 0$. We describe each set of moments in turn. We define the sample analogs of these moments as Φ^1 through Φ^5 and stack them in Φ. This leads to the following GMM objective:

$$\min_{\gamma} \Phi'(\gamma) W \Phi(\gamma)$$

where W is a consistent estimator of the inverse of the asymptotic variance–covariance matrix of the moments. Note that the weighting matrix is block diagonal because we match three different samples: vehicle purchase data, public charging data, and insurance data on mileage. We minimize the objective function with respect to the nonlinear parameters γ.[14]

Aggregate Moments We obtain market shares as $\sigma_{jgt} = \frac{\text{Registrations}_{jgt}}{L_{gt}}$, where we derive the potential market size L_{gt} from the survey responses on total car ownership. We assume

[14]The linear utility parameters are obtained in the estimation loop through the contraction mapping as in Nevo (2001).

households retain vehicles for seven years and therefore set L_{gt} equal to the total number of cars owned in gt divided by seven.[15]

We model the indirect utility in (3) by including prices (accounting for subsidies), range, charging station density measured as the logarithm of charging stations per one thousand households, vehicle size measured as volume, acceleration measured by the ratio of horsepower to weight, and the number of doors as attributes. We also include a rich set of fixed effects at the vehicle segment, body type, fuel type, firm, state, and year level.

We construct instruments that shift vehicle markups, production costs, and charging station entry to address the endogeneity issues. We compute differentiation IVs from vehicle horsepower, fuel economy, and fuel type following Gandhi and Houde (2019). We add the PPP-adjusted exchange rate between Germany and each production country, interacted with vehicle weight as in Grieco, Murry and Yurukoglu (2024). We further interact vehicle weight with a yearly metal price index as a cost shifter. For charging density, we use construction land prices, varying by market and year, and cumulative state-level investment subsidies.

We rely on variation in market shares and fuel/electricity cost distributions across markets to identify the usage cost parameters, constructing proxies to the "most powerful" instruments of Lesellier, Boucher and Gökkoca (2023). Specifically, we add the quartiles of $A_{ijgt}^{l_i=0}$, $A_{ijgt}^{l_i=1}$, $H_{ijgt}^{l_i=1}$, and fuel costs–denoted, for example, $Q_{0.25}(A_{jgt}^{l_i=0})$–in the instrument set. These instruments capture the shape of the distribution of electricity and fuel expenses across individuals.

Charging Moments To match observed charging patterns in the data, we construct a moment that matches model-predicted charging with observed average station usage at five-minute intervals by state and year. This moment is crucial because the timing and amount of public charging jointly determine the implied level of home charging: the two must sum to the total electricity demand from EVs.

Formally, let e_{Gts}^{a} denote the observed aggregate station charging in state G from the stock of EVs at time t and interval s. We impose:

$$e_{Gts}^{a} = \sum_{g \in G} \sum_{i} \sum_{k=2016}^{t} \sum_{j \in \chi_{ik}} e_{ijgks}^{*a} \pi_{ig} L_{gk} \sigma_{ijgk} + \eta_{Gts}.$$

Here e_{ijgks}^{*a} denotes model-predicted charging demand for each individual-vehicle combination at the regional level for newly sold EVs in year k, i.e., the flow of EVs. We aggregate over regions g in each state G, over past EV sales (flows) up to year t, and over individuals and

[15] According to European Automobile Manufacturers Association (ACEA), the average age across EU vehicles is 12.3 years, including second hand vehicles.

vehicles. The error term η_{Gts} captures the remaining difference between the model-implied and observed charging.

We match the public charging demand for calendar years 2019 and 2021, the two years with reliable data.[16] The station charging data cover only subsidized charging stations, except in Hamburg, where we observe usage at all stations. We use Hamburg to rescale subsidized-station data to total charging demand. Further adjustments are required because the model is limited to private EV owners, whereas the charging data are based on all EV owners, see Appendix A.2.

Mileage Moments To identify which travel profiles adopt EVs, we match information on average mileage by fuel type in a given year as reported in the insurance records. This allows us to attribute high- and low-mileage types to different vehicle fuel technologies and to pin down EV buyers' mileage and thus their charging profiles. Specifically, we use survey evidence on average gasoline, diesel, and electric vehicle mileage for new vehicles sold in 2021 and match these average mileages to the model-predicted counterparts for the 2021 sales:

$$\bar{m}_t^{EV} = \sum_g \sum_i \sum_{j \in \chi_{it}} \mathbb{1}\{EV_j = 1\} \pi_{ig} L_{gt} \sigma_{ijgt} m_i + \eta_t^{m,EV},$$

where π_{ig} are the population weights of profile i and m_i is the profile's annual distance traveled. We match $\bar{m}_t^{gasoline}$ and $\bar{m}_t^{diesel}$ in the same way.

4.3 Empirical Model of the Electricity Market

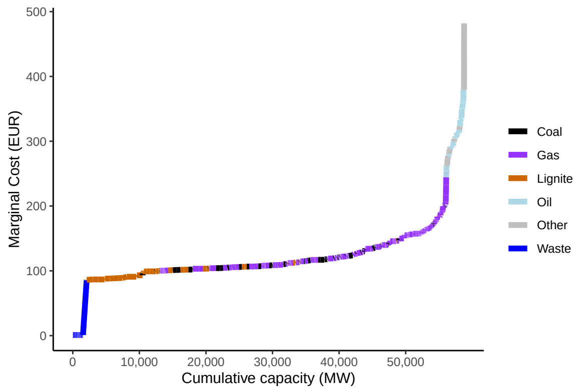
We combine the hourly net load with a merit order model to obtain the equilibrium wholesale price for each of the 8,760 hourly observations per year.

The model is an extension of the merit order tool provided by EWI (for documentation of the tool, see Institute of Energy Economics at the University of Cologne , EWI). We obtain the net load by subtracting realized renewable generation from the hourly load. We build an estimate of every thermal generation unit's marginal cost in the German electricity market to construct the merit order. The marginal cost of generator u is a function of fuel price including transport costs, the emissions factor, other variable costs, and a unit's efficiency:

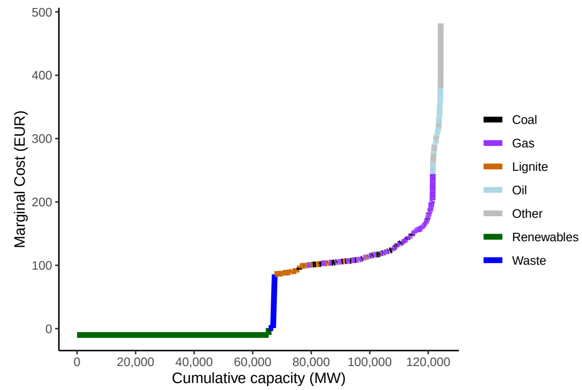
$$c_u = \frac{\text{fuel price}_u}{\text{efficiency}_u} + EUA \times \frac{\text{emissions factor}_u}{\text{efficiency}_u} + \text{variable costs}_u,$$

[16] Data for 2018 are incomplete because the data collection started in that year, and charging demand in 2020 is distorted by COVID-related restrictions. The model holds travel profiles fixed over time; since the time-use survey is a cross-section, we cannot account for pandemic-induced changes in travel or charging in 2020.

Figure 5: Merit order curves with no and maximal renewable generation



No renewable generation



Maximum observed renewable generation

Note: The figure plots the merit-order curve without renewable generation (left) and with maximum renewable generation (right). Generators are ordered by marginal cost c_u, and the cumulative capacity is plotted on the horizontal axis.

where EUA denotes the EU Emissions Trading System (ETS) allowance price, which we set to €83.66 per t/CO_2, the average price for 2023. The data reports generator-specific efficiency rates and Appendix Table A1 details the other determinants of marginal costs. Appendix Figure A2 plots the distribution of marginal costs c_u by generation type. We set the capacity of each plant equal to the gross generation capacity corrected for the unavailability rate of plant u, defined as the fraction of time unit u is unavailable due to maintenance or unplanned outages.

Figure 5 shows two merit orders: one without any renewable generation (left panel) and one with the highest amount of renewable generation that we observe in 2023 (right panel). In the left panel, lignite plants come online first (aside from a small amount of waste-based generation). Once their capacity is exhausted, a mix of hard coal and gas plants follow. Hard coal tends to have a lower marginal cost but is also more emissions-intensive, making its marginal cost comparable to gas plants due to the CO_2 price. Marginal costs then rise more steeply as the most expensive gas plants come online and ultimately spike towards €500/MWh as oil peakers are dispatched.

The right panel of Figure 5 shows that renewables can double available capacity in the most favorable hours. There are some hours when renewable generation is sufficient to meet the load and electricity is zero-emission. In those cases, we assume the wholesale price equals €-10/MWh. This reflects the fact that negative bidding is common in such hours since renewable generation units receive subsidies, making it profitable to supply electricity even at negative prices. When renewables cannot cover the market by themselves, prices

Table 1: Unconditional average fueling and charging expenses (€ per day)

	Fuel Expense	Public Charging		Home Charging
	C^{ICE}	$A^{l=0}$	$A^{l=1}$	$H^{l=1}$
All cars:	€ 2.71 (3.87)	€ 1.94 (2.24)	€ 2.45 (3.03)	€ 1.14 (1.25)
VW Golf super:	€ 2.65 (3.52)	–	–	–
VW Golf diesel:	€ 2.02 (2.69)	–	–	–
VW up!:	–	€ 1.43 (1.50)	€ 1.82 (2.01)	€ 0.84 (0.82)
Tesla Model Y:	–	€ 2.88 (3.22)	€ 4.17 (5.82)	€ 1.59 (1.70)

Notes: The table reports unconditional average daily operating expenses across all 11 million travel profile–vehicle-region combinations, irrespective of vehicle choice. Standard deviations between brackets. Fuel costs (C^{ICE}) are based on ICE vehicles using regional fuel prices and vehicle-specific consumption. Charging costs are computed from the charging model: $A^{l=0}$ is public charging for consumers without home access; $A^{l=1}$ is public charging for consumers with home access; $H^{l=1}$ is home charging for consumers with home access. A dash indicates not applicable. All values are in euros per day.

jump to around € 100/MWh as thermal units come online.

5 Results

5.1 Charging Model Solution

Table 1 reports the average daily cost of charging for EVs and refueling for combustion vehicles. These averages are unconditional across all travel profile–vehicle combinations, irrespective of vehicle choice. BEVs can technically satisfy almost all weekly travel profiles, only 1% of individuals have at least one BEV excluded from their choice set.

For combustion vehicles, the average daily fuel costs is € 2.7 with a standard deviation of 3.9. This variation reflect both differences in fuel economy—for example, a VW Golf Super costs € 2.7 per day and a VW Golf Diesel € 2—and variation in mileage across travel profiles. Average home-charging expenses are only € 1.1, indicating that EVs are cheap to operate when charged at home; charging a Tesla Model Y at home is cheaper than operating a VW Golf diesel. In contrast, charging at stations is considerably more expensive due to high markups over retail electricity prices. Charging a Tesla Model Y entirely at stations is more costly than operating a VW Golf super.

For consumers with home-charging access, away-charging expenses $A_{ijgt}^{l_i=1}$ are even higher. This is driven by outliers: very high-mileage consumers who cannot cover their demand with home charging alone and must rely heavily on stations.

5.2 Demand Estimates

The estimates in Table 2 indicate that consumers value vehicle volume and acceleration (power). For EVs, range and charging-station density have positive coefficients, consistent with adoption increasing as battery capacity improves and charging infrastructure expands. The Logit OLS results show the price and charging density coefficients before instrumenting. With instruments, the mean price elasticity is -2.5 using the price instruments described above, comparable to previous estimates for Germany in the same period (see Remmy, 2025; Alé-Chilet, Chen, Li and Reynaert, 2025; Miravete, Moral and Thurk, 2018). The fuel-type fixed effects (not reported) reveal gasoline as the most preferred fuel type conditional on all controls, followed by HEVs and PHEVs, while diesel and especially BEVs are less preferred.

The fuel expense parameters are γ^h, γ^a, and γ^{ICE}. Table 2 first shows estimates based on the aggregate sales moments Φ^1 and then shows results when we include the micro-moments Φ^2–Φ^5, which match station charging and mileage by fuel type (EV, gasoline, diesel). We find that consumers strongly dislike expenses at public charging stations. They also dislike home-charging expenses (γ^h) even more than combustion-fuel expenses (γ^{ICE}).

The additional moments Φ^2–Φ^5 are crucial for identifying these parameters. Without them, only variation in driving profiles and EV market shares is available to infer which profiles adopt EVs. The extra moments force the model to assign different disutilities to home and away charging so that the predicted amount of charging matches the observed station usage in each market.

The model estimated without the micro-moments Φ^2–Φ^5 predicts that 30% of BEV buyers lack home-charging access and that these drivers commute on average 13.1 km per day. This implies electricity demand that is too high relative to observed station usage. When we impose the additional moments Φ^2–Φ^5 matching charging and mileage, the estimation raises the disutility from station charging. High-mileage consumers who rely on public chargers then adopt fewer EVs: their share falls to 24% and their average commute drops to about 12.9 km per day.

Correspondingly, the share of buyers with home-charging access rises from 70% to 76%, and their average daily mileage increases by 8 km. To match the high average EV mileage in the micro-moment, the home-charging valuation parameter γ^h declines from above 2 to about 1.5. We use the full model with micro-moments Φ^1-Φ^5 for all subsequent computations.

The charging model and demand estimation results together allow us to predict home and public charging throughout the day, plotted in Figure 6. The public charging (left panel) closely matches the observed curve in Figure 3, as this is targeted by the micro-moment Φ^2. The only noticeable difference appears in the early morning and reflects our assumption that

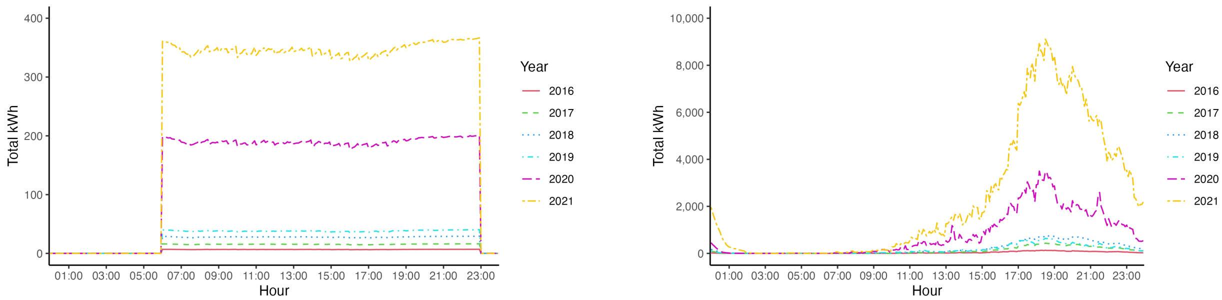
Table 2: Demand Estimates

	Logit OLS		**Only Φ_1**		$\Phi_1 - \Phi_5$	
Variable	Coeff.	St.Err.	Coeff.	St.Err.	Coeff.	St.Err.
Taste parameters (α, β):						
Price	-0.022	0.001	-0.067	0.002	-0.068	0.003
Range	0.002	0.000	0.002	0.000	0.002	0.000
Charging station density	0.578	0.020	0.707	0.032	0.671	0.044
Volume	0.043	0.005	0.162	0.007	0.173	0.007
Acceleration	-0.013	0.000	-0.002	0.000	-0.002	0.001
Number of doors	-0.131	0.006	-0.078	0.007	-0.062	0.009
Constant	-12.065	0.121	-8.867	0.061	-8.666	0.063
Fuel and Electr. Cost parameters:						
γ^h	-0.001	0.003	-0.026	0.008	-0.019	0.001
γ^a	-0.014	0.003	-0.039	0.012	-0.041	0.001
γ^{ICE}	-0.015	0.002	-0.010	0.000	-0.013	0.000
Statistics:						
Mean price elasticity	-0.801		-2.424		-2.455	
Share of BEV owners charging:						
at home			0.707		0.757	
publicly			0.293		0.242	
Average mileage (in km):						
BEV (charging at home)			25.335		33.254	
BEV (charging publicly)			13.103		12.937	
ICE			25.155		23.981	
Valuation of energy costs relative to car price:						
BEV (charging at home)			2.295		1.628	
BEV (charging publicly)			3.453		3.614	
ICE			0.913		1.173	

Notes: The table reports demand estimates from a random-coefficients logit model estimated by GMM. Fixed effects are included for fuel type (gasoline as reference; diesel, PHEV, BEV, and HEV dummies), car class, body type, manufacturer, state, and year. Estimation relies on three sets of moments: (i) Φ_1 aggregate market-share moments with differentiation instruments, vehicle cost shifters, "most powerful" usage-cost instruments, and charging-station cost shifters; (ii) Φ_2 state-level moments matching observed public charging at five-minute intervals; and (iii) Φ_3 mileage moments matching average mileage by fuel type from insurance data.

no station charging occurs between 11 p.m. and 6 a.m.

Figure 6: Mean model-implied EV charging over the day



Public charging

Home charging

Note: The figure plots model-implied public charging (left panel) and home charging (right panel). We obtain these load curves from the demand estimates and the cost-minimizing charging profiles.

The right panel of Figure 6 shows model-predicted home charging when drivers plug in and begin charging immediately upon arriving home. Home charging is concentrated in the early evening, with a pronounced peak between 5 p.m. and 7 p.m. and almost no charging later at night, since EVs typically need less than one hour of evening charging to fully recharge.

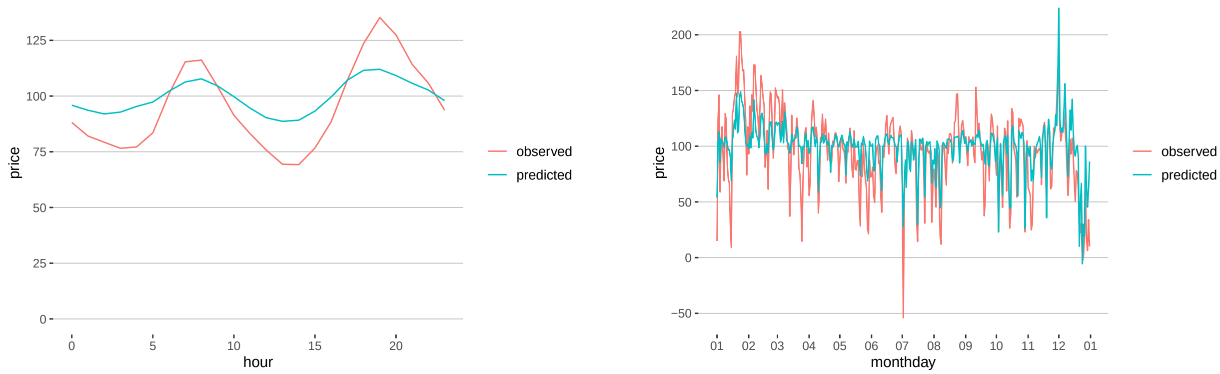
5.3 Electricity Market Simulations

We benchmark the empirical electricity market model against observed 2023 day-ahead wholesale prices. The observed yearly average spot price in 2023 was €95.18, while the model predicts €107.50. The correlation between predicted and actual hourly spot prices is 0.72. Given the model's simplicity, this is a strong fit. For comparison, Andrés-Cerezo and Fabra (2025) study the Spanish electricity market and find a correlation of 0.87.[17]

Figure 7 compares average intraday spot prices, actual and model-predicted. The model produces a flatter load–price curve than observed, a common outcome when assuming perfect competition and ignoring ramp-up costs. The figure also shows average daily spot prices over the year. Here again, the model predicts a flatter profile with less variance than observed, but it tracks overall price movements well except during extreme negative-price events. Such events arise because feed-in subsidies make it profitable for renewable units to supply even at strongly negative prices, and some thermal generators prefer to sell at negative prices rather than incur high ramp-down and ramp-up costs.

[17] Andrés-Cerezo and Fabra (2025) simulate the Spanish market for 2019, a period with fewer hours of negative prices and lower market volatility.

Figure 7: Comparison of observed and predicted wholesale prices



Intra-day prices

Average daily prices

Note: The figure plots observed and model-predicted intra-day electricity prices (left panel) and observed and model-predicted average daily electricity prices (right panel).

6 Quantifying the Joint Equilibrium of EV and Electricity markets

In this section we compute the joint equilibrium of the EV and electricity markets, capturing the feedback whereby higher EV adoption raises electricity prices and thereby reduces consumers' willingness to buy an EV. We then examine how the equilibrium changes when electricity pricing moves from Germany's current flat-rate scheme to time-varying tariffs. Finally, we study how the equilibrium responds to renewable-energy entry, increases in electricity demand (for example from data centers), and higher carbon prices.

Simulation Details The demand model predicts annual vehicle sales (flows), but the joint equilibrium depends on the stock of EVs. For each scenario we therefore begin from an EV stock equal to 10% of the vehicle fleet: 4.8 million EVs. By the end of 2021, 618,460 EVs were on the road in Germany; by the end of 2024, 1.65 million. The government targets 15 million by 2030. We view a 10% stock as a realistic scenario for the next three to five years, before structural shifts in electricity supply occur.

We obtain this stock by multiplying the 2021 flow of EV sales by a fixed factor of 27.51.[18] Our approach ensures that the starting stock is internally consistent with the observed 2021 demand and does not require us to model the dynamic buildup of the EV fleet.

The final equilibrium stock may differ depending on the strength of the feedback loop, since EV sales respond to electricity prices. To maintain comparability across scenarios, we

[18] In 2021 our sample contains 174,461 EV sales. With roughly 48 million registered vehicles, a 10% EV share corresponds to 4.8 million EVs. Thus $0.10 \times 48{,}000{,}000/171{,}461 \approx 27.51$.

scale flows by the same fixed factor, ensuring the initial stock corresponds to a 10% share. We then compare this equilibrium to a reference market in which no EVs are present.

We take the observed load, renewable generation, and merit order from calendar year 2023 as the baseline. Below, we discuss scenarios where base demand or renewable generation supply increase.

For each counterfactual, we begin from the 2021 vehicle market equilibrium and scale the sales quantities by the fixed factor. We then compute the implied EV load curves and derive a new electricity market equilibrium.[19] This first step abstracts from the feedback between the vehicle and electricity markets. We report results from this intermediate step to quantify the importance of accounting for the feedback loop. In the next step, we iterate between updating the vehicle and electricity market equilibria until convergence is reached and the equilibrium conditions in (3.5) are satisfied.

We consider two pricing schemes in the counterfactuals. In the first, electricity rates remain fixed intraday, as is currently the case in Germany. In this scenario, consumers face no intraday incentives to shift charging and we assume home-chargers plug in upon arrival at home. Because the tariff schedule does not vary within the charging period S, we do not need to recompute the solution of the charging model. Instead, we update the electricity expense terms that enter demand, which in turn affect market shares and implied load curves. We then iterate between the vehicle and electricity markets until convergence. While the timing of charging is unchanged for each individual, equilibrium EV choice probabilities and aggregate EV load do change.

In the second scheme, we implement time-varying prices for EV home chargers. While such tariffs are not yet available in Germany, policy aims to facilitate their rollout, and it is technologically feasible to install timers on home chargers to automate cost-minimizing charging.[20] The time-varying scheme assumes perfect responsiveness from consumers, e.g. with automated smart meters, and can therefore be interpreted as the scenario in which EV buyers are most responsive to wholesale price variation.

We implement time-varying prices by setting $p_s^h = p_s^w + \mu^h$ and re-solve the battery cost-minimization problem whenever the price sequence changes.[21] This requires iterating

[19] We calculate the electricity load from EV's as $E^{EV} = \sum_g \sum_i \sum_{j \in \chi_i} \pi_{ig} e^*_{ijgs} \Gamma L_{gk} \sigma_{ijg}$ in which we take $\sigma_{ijg} = \sigma_{ijgt=2021}$, Γ is the fixed factor scaling EV quantity in 2021 up to 4.8 million units, and π_{ig} are the type population weights described in Footnote 11. Both e^*_{ijgs} and σ_{ijg} are endogenous in the counterfactual.

[20] A recent bill to accelerate the deployment of smart meters underlines this policy direction. Upon its adoption, Germany's Federal Minister for Economic Affairs and Climate Action, Robert Habeck, stated: "Expanding renewable energy on the one hand and making increased use of electric vehicles in the transport sector and of heat pumps in buildings on the other requires us to connect electricity generation and demand in an intelligent way." Federal Ministry for Economic Affairs and Climate Action (BMWK)

[21] We build two different intra-day price curves for winter and summer months to reflect differences in wind and solar output throughout the year.

between the charging, vehicle, and electricity market equilibria until convergence. A complication is the occurrence of "shadow peaks" (Bailey, Brown, Myers, Shaffer and Wolak, 2024), where all EVs shift to the lowest-price hour, which then changes in the next iteration. To mitigate this, we randomly allocate the lowest price across the eight cheapest hours, effectively spreading load across them. This pragmatic approximation mimics a real-world load management decision to spread the load across low-price periods.[22]

For each scenario, we report changes in electricity generation and prices and EV sales and prices. We also compute total generation costs—given by the sum of marginal costs times generation across all plants—and total emissions. Because our model identifies exactly which generators supply the additional EV demand, we can report the resulting CO_2 emissions from the additional load caused by EVs. We also compute annual CO_2 emissions from the vehicle fleet, taking into account that EVs substitute for ICE vehicles and the outside good.[23] Most previous studies instead rely on average emissions intensities.

We also compute electricity expenditures and decompose total expenditures into charging expenditures and a pecuniary externality (the spillover from higher electricity prices on base demand). Specifically, we define the change in electricity expenditure as:

$$\underbrace{\sum_{s}^{S}(E_s^B(p_{s,post}^w + \mu) + E_s^{EV,h}p_{s,post}^h + E_s^{EV,a}p_{s,post}^a) - E_s^B(p_{s,pre}^w + \mu))}_{\text{Change in Electricity Expenditure}}$$

$$= \underbrace{\sum_{s}^{S}(E_s^{EV,h}p_{s,post}^h + E_s^{EV,a}p_{s,post}^a)}_{\text{Charging expenditure}} + \underbrace{\sum_{s}^{S}(E_s^B(p_{s,post}^w - p_{s,pre}^w))}_{\text{Pecuniary externality}},$$

where we use $E_{s,post}^B = E_{s,pre}^B$, $E_{s,pre}^{EV} = 0$, and μ is constant. The pecuniary externality captures the extent to which EV adoption indirectly redistribute costs to non-EV users via higher base load bills. The formulation highlights the pecuniary externality of EV charging on other electricity users will be most pronounced when EV-induced price increases coincide with high-demand periods.

[22]Even with this randomization, the solution oscillates between two minor shadow peaks with nearly identical outcomes. We report results for one outcome and present both in the Appendix Table A2.

[23]Because we focus on new sales, the outside good captures either keeping an existing vehicle or not driving. We assign the outside good the average emissions intensity of ICE vehicles, as existing vehicles likely pollute more, while not purchasing a new vehicle (e.g., relying on public transport) likely entails lower emissions. We focus on CO_2 emissions and ignore reductions in local pollutants. Adding local pollutants would require modeling air pollution as in Holland, Mansur and Yates (2021)

Table 3: Electricity, Vehicle, Emissions, and Expenditures Outcomes

		Fixed price		**Time-varying price**	
	No EVs	No feedback	Full eq.	No feedback	Full eq.
	(1)	(2)	(3)	(4)	(5)
Electricity Market:					
Generation (TWh)	459.42	+7.37	+7.28	+7.37	+7.71
Weighted price (EUR/mWh)	106.72	+2.67	+2.64	+2.07	+2.21
Generation cost (bil EUR)	19.60	+0.82	+0.81	+0.74	+0.77
Vehicle Market:					
EV sales (1,000 units)	0	4,800	4,772	4,800	4,900
EV price	-	35,172	35,172	35,172	35,172
Emissions:					
Grid emissions (mio t)	158.21	+4.91	+4.85	+5.16	+5.41
Vehicle emissions (mio t)	61.94	-0.70	-0.76	-0.48	-0.36
EVs: gCO2/km	-	91.27	90.20	94.87	95.00
Expenditures:					
EV charging (bil EUR)	-	+1.79	+1.79	+1.73	+1.80
Baseline (bil EUR)	49.08	+1.22	+1.21	+0.95	+1.01

Notes: Column (1) reports the baseline equilibrium without EVs. Columns (2) and (4) "No feedback") adjust electricity supply in response to a 4.8 million EV stock but hold vehicle demand fixed. Columns(3) and (5) ("Full eq.") allow the full feedback loop between electricity and vehicle markets. "Weighted price" is the average load-weighted wholesale price. "Other expenditure" denotes the pecuniary externality from EV-induced electricity price increases on baseline consumption.

6.1 The Feedback Loop with Fixed and Time-Varying Electricity Rates

Table 3 reports the effects of a 10% EV stock on the electricity and vehicle markets. Column (1) shows the baseline without EVs. Columns (2) and (4) ("No feedback") report outcomes when the electricity market adjusts to additional EV load but vehicle demand is held fixed. Columns (3) and (5) ("Full equilibrium") allow the full feedback loop: higher electricity demand raises wholesale prices, which in turn affects EV adoption and vehicle market equilibrium. We report results under flat-rate pricing and time-varying pricing.

Comparing columns (1) and (2) of Table 3 shows that a 10% EV stock (4.8 million vehicles) requires about 7 TWh of additional electricity and raises wholesale prices by €2.67/MWh, or 2.5%. EV adoption increases CO_2 emissions from the electricity sector by 4.9 million tonnes. These emissions replace ICE emissions and, therefore, total vehicle emissions decrease by 0.70 million tonnes or 1.1%. This is a small decrease. EVs emit more than 90gCO_2/km because they are often powered by gas and coal. As a comparison, the current EU fleet emissions target is 95gCO_2/km.[24] EVs actual emissions would thus barely help with reaching the 95gCO_2/km target for firms if the EU would assign actual CO_2/km in the computation of the standard. In practice, the EU counts EVs as zero-emission vehicles, implicitly assuming they are always powered by renewable energy. EV users spend €1.8 billion on charging. Strikingly, expenditures by non-EV users also rise by €1.2 billion due to higher electricity prices, indicating a sizable pecuniary externality. A 2.5% increase in electricity prices is thus economically meaningful at the macro level.

Column (3) introduces the full feedback loop. The results show that EV adoption responds little to the electricity price increase. A 2.6% rise in electricity prices is too small to offset the substantial operating-cost advantage of EVs documented in Table 1. Vehicle prices remain unchanged, and emissions and expenditure outcomes are virtually identical to the no-feedback case.[25] This finding is central: as EV purchase prices fall, many drivers will adopt EVs because of their lower operating costs. This expansion will raise electricity prices and generate sizable pecuniary externalities, but our results suggest that electricity price increases are not sufficient to materially constrain EV adoption since the cost gap with combustion vehicles remains large.

Column (4) introduces 4.8 million EVs that charge in response to wholesale prices rather than upon arrival at home. Before incorporating the feedback loop, time-varying prices reduce generation costs from €0.82 billion to €0.74 billion. Lower system costs translate into less upward pressure on electricity prices, so both charging expenditures and the pecuniary externality are smaller than under flat pricing. Interestingly, EVs emit more under time-varying pricing. This reflects Germany's 2023 merit order: coal is typically dispatched before expensive gas, and renewable sources are not marginal during many nighttime hours. With flat prices, EVs charge more often when gas sets the marginal price, resulting in lower average emissions despite higher costs.

Column (5) shows that the apparent cost savings from time-varying pricing shrink once the full feedback loop is taken into account. Access to lower off-peak prices—often more than 20% below the flat tariff—reduces charging costs for many EV buyers, widening the operating cost advantage of EVs relative to ICE vehicles. As a result, EV adoption increases by over 100,000 units. The additional demand raises electricity prices, such that total generation costs and the pecuniary externality converge to levels closer to those under flat pricing. Overall, time-varying prices encourage EV adoption but only partially alleviate the upward pressure that EVs place on the electricity market.

[24]The EU emission standards specific a sales-weighted emission target for each firm. When the target is not reached, firms must pay penalties per vehicle sold. See Reynaert (2020).

[25]Vehicle prices are endogenized in the model, but equilibrium adjustments are negligible.

Table 4 reports changes in generation profits across energy sources. The total increase in electricity-sector profits arises from two channels: (i) margins on the additional electricity sold to EVs, and (ii) higher margins on the pre-existing base load, reflecting the pecuniary externality from EV-induced price increases. Overall profits rise by about 3.5% in equilibrium, with slightly smaller gains under time-varying prices than under fixed prices.

The distribution of profit gains across technologies differs sharply. While the feedback loop has little effect on relative profits (compare columns (2)–(3) and (4)–(5)), the pricing regime matters greatly. Under fixed prices, renewables' profits rise by only 1.6%, whereas coal and gas profits increase by 23% and 28%, respectively. Because profits accrue to inframarginal generators, these results indicate that most of the EV-induced price increases occur when higher-cost coal and gas are at the margin and lower-cost coal and gas inframarginal. Under time-varying prices, the pattern changes: renewables' profits nearly double to 2.5%, while those of coal and gas fall by half. Time-varying pricing shifts EV load toward hours with higher renewable output, raising prices and rents when renewables are inframarginal but not increasing rents for fossil units in the hours they produce.

At first glance, these results may seem inconsistent with Table 3, where we find that EV emissions are higher under time-varying pricing. The apparent contradiction stems from the distinction between inframarginal and marginal producers: emissions are determined by marginal sources, while profits accrue to inframarginal ones. Hence, although time-varying pricing increases short-run emissions, it strengthens the profitability—and therefore the investment incentives—of renewable producers relative to fossil generators. Our empirical equilibrium is a first necessary step towards understanding longer term investment incentives. Because entry into the electricity market is highly regulated, depends on available network capacity, and on investors' long run expectations of the EV stock we consider endogenous entry out of the scope of this paper.

6.2 EV adoption and electricity market transition

Table 5 examines three scenarios reflecting ongoing transitions in the electricity market. First, we more than double the carbon price in the EU Emissions Trading System (ETS) to €200/tCO_2. Second, we expand renewable generation capacity by 10%, consistent with current German policy goals. Third, we increase the hourly electricity load by 10%, representing demand growth from electrification of other sectors (e.g., heating, industry, or data centers) in the absence of new generation capacity.

When we increase the ETS price, EV adoption declines markedly under fixed electricity rates. Generation for EVs falls by roughly 30%, and EV sales drop by 8%, while charging

Table 4: Changes in Generation Profits by Energy Source

		Fixed price		Time-varying price	
	No EVs (1)	No feedback (2)	Full eq. (3)	No feedback (4)	Full eq. (5)
Total (bil EUR)	29.42	+4.06%	+4.02%	+3.44%	+3.65%
Profits by source:					
Renewables (bil EUR)	24.30	+1.85%	+1.84%	+2.79%	+2.97%
Lignite (bil EUR)	2.15	+11.82%	+11.69%	+6.05%	+6.40%
Coal (bil EUR)	0.72	+25.58%	+25.33%	+10.08%	+10.75%
Gas (bil EUR)	0.85	+31.50%	+31.20%	+11.78%	+12.60%

Note: Profits are in billion euros. Column (1) reports the baseline equilibrium without EVs. Columns (2) and (4) ("No feedback") adjust electricity supply in response to a 10% EV stock while holding vehicle demand fixed. Columns (3) and (5) ("Full equilibrium") allow for the complete feedback between vehicle and electricity markets. Profit changes are expressed as percentage deviations from the baseline.

expenditures and the pecuniary externality remain almost unchanged. The decline in adoption arises because higher ETS prices raise wholesale electricity costs during most hours when renewables are not marginal. Consequently, electricity becomes relatively more expensive than fuels, reducing the incentive to adopt EVs and shifting adoption away from high-mileage drivers.[26] Under time-varying prices, these effects are somewhat mitigated: EV users can avoid hours most affected by the ETS increase. Total EV-related emissions fall in both pricing regimes, as higher ETS prices tighten the correlation between generators' marginal costs (including ETS carbon permit costs) and their CO_2 intensity. However, EVs are not cleaner in terms of gCO_2/km because adoption shifts to lower mileage types.

In the renewable-expansion scenario, increasing renewable capacity by 10% boosts EV adoption under both pricing regimes. Under fixed prices, greater renewable entry initially lowers EV emissions because additional green generation directly powers EVs, but as adoption expands, total generation rises and fossil sources again set the margin. Time-varying prices amplify these effects: lower renewable-hour prices are passed through to EV charging, further stimulating adoption while keeping total emissions largely unchanged.

In the demand-expansion scenario, higher non-EV electricity demand reduces EV adoption due to elevated electricity prices. The pecuniary externality becomes substantial—€1.70 billion compared to €1.77 billion in charging expenditure. Under time-varying prices, the reduction in adoption is much smaller, and the pecuniary externality declines to €1.1 billion for nearly identical charging expenditure. Although increased demand without additional

[26] Fuel prices are kept constant, so this scenario can also be interpreted as an increase in electricity prices relative to fuel prices.

Table 5: EV Adoption and Electricity Market Transition Scenarios

	No EVs	Baseline	ETS	Renewables	Demand
			Fixed price		
Electricity Market:					
Generation (TWh)	459.42	+7.28	+5.12	+7.58	+6.70
Weighted price (EUR/mWh)	106.72	+2.64	+2.50	+2.58	+3.37
Generation cost (bil EUR)	19.60	+0.81	+0.99	+0.80	+0.78
Vehicle Market:					
EV sales (1,000 units)	0	4,772	4,014	4,868	4,579
EV price	-	35,172	35,176	35,172	35,172
Emissions:					
Grid emissions (mio t)	158.21	+4.85	+3.60	+5.00	+4.22
Vehicle emissions (mio t)	61.94	-0.76	-1.05	-0.73	-1.15
EVs: gCO2/km	-	90.20	94.61	89.31	85.11
Expenditures:					
EV charging (bil EUR)	-	+1.79	+1.68	+1.80	+1.77
Baseline (bil EUR)	49.08	+1.21	+1.15	+1.18	+1.70
			Time-varying price		
Electricity Market:					
Generation (TWh)	459.42	+7.71	+5.52	+8.16	+7.40
Weighted price (EUR/mWh)	106.72	+2.21	+2.68	+2.53	+2.19
Generation cost (bil EUR)	19.60	+0.77	+0.97	+0.75	+0.81
Vehicle Market:					
EV sales (1,000 units)	0	4,900	4,163	5,018	4,802
EV price	-	35,172	35,174	35,172	35,172
Emissions:					
Grid emissions (mio t)	158.21	+5.41	+3.30	+5.43	+4.97
Vehicle emissions (mio t)	61.94	-0.36	-1.54	-0.49	-0.68
EVs: gCO2/km	-	95.00	80.26	91.16	90.18
Expenditures:					
EV charging (bil EUR)	-	+1.80	+1.71	+1.80	+1.79
Baseline (bil EUR)	49.08	+1.01	+1.23	+1.16	+1.11

Note:
Column (1) and (2) replicate the baseline equilibrium without and with EVs (as in Table 3). Columns (3)–(5) simulate the joint equilibrium of the vehicle and electricity markets under different transition scenarios: (3) an increase in the ETS price to €200 per tonne of CO_2 (4) an increase in renewable capacity of 10% (5) a uniform 10% increase in demand in all periods. "Weighted price" denotes the average load-weighted wholesale price. "Other expenditure" refers to the pecuniary externality—i.e., the change in electricity costs for baseline consumers resulting from EV-induced price increases.

generation drives up average electricity prices, time-varying prices allow EV owners to shift load to low-price hours, making EV adoption more compatible with other sources of electrification such as heating or data centers.

In sum, time-varying electricity prices play an important role in sustaining EV adoption throughout the ongoing energy transition. They buffer EV users from price increases driven by higher carbon costs or growing demand and allow them to benefit more from renewable expansion.

7 Conclusion

We develop and estimate a joint equilibrium model linking vehicle adoption, individual charging decisions, and electricity market outcomes. The model unifies the vehicle and electricity markets through the charging decision, allowing us to quantify how EV adoption feeds back into electricity prices and how electricity pricing regimes shape vehicle adoption.

A 10% EV stock increases wholesale electricity prices by about 2%, creating a substantial pecuniary externality on other electricity users. This price increase has little impact on EV adoption, as the operating cost advantage of EVs over combustion vehicles remains large. Introducing time-varying electricity prices changes both the timing and cost of charging: it flattens the load curve and lowers generation costs when adoption is held fixed. However, once we account for the feedback between markets, the lower charging costs stimulate additional adoption, raising electricity demand and returning generation costs and price levels close to those observed under flat pricing. Time-varying prices thus encourage adoption but do not, in equilibrium, fully mitigate the aggregate price pressure on the electricity market.

We further study how the broader energy transition interacts with EV adoption. Higher carbon prices reduce EV adoption under fixed rates but less under time-varying prices, where drivers can avoid high-price hours. Renewable expansion increases adoption–especially under time-varying prices–while additional electricity demand from other sectors reduces adoption and amplifies pecuniary spillovers, again partly offset when prices vary over time.

Overall, our findings suggest that EVs and electricity markets are strongly complementary: adoption affects electricity prices, and electricity pricing in turn shapes who buys EVs and when they charge. Time-varying prices are effective at directing load to cleaner, cheaper hours and sustaining adoption during the transition, but they do not eliminate the aggregate pecuniary externalities from the electrification of private transport.

References

Alé-Chilet, Jorge, Cuicui Chen, Jing Li, and Mathias Reynaert. 2025. "Colluding against environmental regulation." *Review of Economic Studies*.

Allcott, Hunt, and Nathan Wozny. 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *The Review of Economics and Statistics*, 96(5): 779–795.

Andrés-Cerezo, David, and Natalia Fabra. 2025. "Storage and renewable energies: Friends or foes." *Working Paper*.

Armitage, Sarah, and Frank Pinter. 2025. "Regulatory Mandates and Electric Vehicle Product Variety." *Working Paper*.

Bailey, Megan, David Brown, Blake Shaffer, and Frank Wolak. 2025. "Show Me the Money! A Field Experiment on Electric Vehicle Charge Timing." *American Economic Journal: Economic Policy*.

Bailey, Megan, David P. Brown, Erica Myers, Blake Shaffer, and Frank A. Wolak. 2024. "Electric Vehicles and the Energy Transition: Unintended Consequences of a Common Retail Rate Design." *Working Paper*.

Benetton, Matteo, Giovanni Compiani, and Adair Morse. 2023. "When cryptomining comes to town: High electricity-use spillovers to the local economy." *Working Paper*.

Bernard, L., A. Hackett, R. Metcalfe, L. Panzone, and A. Schein. 2025. "The Impact of Dynamic Prices on Electric Vehicle Public Charging Demand: Evidence from a Nationwide Natural Field Experiment." *Working Paper*.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile prices in market equilibrium." *Econometrica*, 63(4): 841–890.

Burlig, Fiona, James Bushnell, David Rapson, and Catherine Wolfram. 2021. "Low energy: Estimating electric vehicle electricity use." Vol. 111, 430–35.

Bushnell, James B, Erich Muehlegger, and David S Rapson. 2022. "Energy prices and electric vehicle adoption." *Working Paper*.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. "Are Consumers Myopic? Evidence from New and Used Car Purchases." *American Economic Review*, 103(1): 220–56.

Butters, R Andrew, Jackson Dorsey, and Gautam Gowrisankaran. 2025. "Soaking up the sun: Battery investment, renewable energy, and market equilibrium." *Econometrica*, 93(3): 891–927.

Chatterjee, Chirantan, Ying Fan, and Debi Prasad Mohapatra. 2024. "Spillover Effects in Complementary Markets: A Study of the Indian Cellphone and Wireless Service Markets." *Working Paper.*

Dorsey, Jackson, Ashley Langer, and Shaun McRae. 2025. "Fueling alternatives: Gas station choice and the implications for electric charging." *American Economic Journal: Economic Policy*, 17(1): 362–400.

European Automobile Manufacturers Association (ACEA). 2024. "Average age of the EU vehicle fleet, by country." https://www.acea.auto/figure/average-age-of-eu-vehicle-fleet-by-country, Accessed: October 22, 2025.

Federal Ministry for Economic Affairs and Climate Action (BMWK). 2023. "The cabinet adopts relaunch of the digitisation of the energy transition and paves the way for accelerated smart meter rollout." https://tinyurl.com/mtd2tcdv, Accessed: October 22, 2025.

Fournel, Jean-François. 2025. "Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions." *Working Paper.*

Gandal, Neil, Michael Kende, and Rafael Rob. 2000. "The dynamics of technological adoption in hardware/software systems: the case of compact disc players." *The Rand Journal of Economics*, 43–61.

Gandhi, Amit, and Jean-François Houde. 2019. "Measuring Substitution Patterns in Differentiated Products Industries." *Working Paper.*

Gillingham, Ken, Marten Ovaere, and Stepanie M. Weber. 2024. "Carbon Policy and the Emissions Implications of Electric Vehicles." *Journal of the Association of Environmental and Resource Economists.*

Grieco, Paul LE, Charles Murry, and Ali Yurukoglu. 2024. "The evolution of market power in the us automobile industry." *The Quarterly Journal of Economics*, 139(2): 1201–1253.

Grigolon, Laura, Eunseong Park, and Kevin Remmy. 2024. "Fueling Electrification: The Impact of Gas Prices on Hybrid Car Usage." *Working Paper.*

Grigolon, Laura, Mathias Reynaert, and Frank Verboven. 2018. "Consumer valuation of fuel costs and tax policy: Evidence from the European car market." *American Economic Journal: Economic Policy*, 10(3): 193–225.

Hausman, Jerry A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics*, 10(1): 33–54.

Holland, Stephen P, Erin T Mansur, and Andrew J Yates. 2021. "The electric vehicle transition and the economics of banning gasoline vehicles." *American Economic Journal: Economic Policy*, 13(3): 316–44.

Holland, Stephen P, Erin T Mansur, and Andrew J Yates. 2022. "Decarbonization and Electrification in the Long Run." *Working Paper.*

Holland, Stephen P, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates. 2016. "Are there environmental benefits from driving electric vehicles? The importance of local factors." *American Economic Review*, 106(12): 3700–3729.

Institute of Energy Economics at the University of Cologne (EWI). 2024. "Dokumentation EWI Merit Order Tool 2023." https://www.ewi.uni-koeln.de/en/publications/ewi-merit-order-tool-2023/, Accessed: October 22, 2025.

International Energy Agency. 2025. "Global EV Outlook 2025."

Jia Barwick, Panle, Hyuk-Soo Kwon, and Shanjun Li. 2024. "Attribute-Based Subsidies and Market Power: An Application to Electric Vehicles." *Working Paper.*

Jia Barwick, Panle, Shanjun Li, Andrew Waxman, Jing Wu, and Tianli Xia. 2024. "Efficiency and equity impacts of urban transportation policies with equilibrium sorting." *American Economic Review*, 114(10): 3161–3205.

Joskow, Paul L., and Catherine D. Wolfram. 2012. "Dynamic Pricing of Electricity." *American Economic Review*, 102(3): 381–85.

Jullien, Bruno, and Matthieu Bouvard. 2022. "Fair cost sharing: big tech vs telcos." *Working Paper.*

Lee, Robin S. 2013. "Vertical integration and exclusivity in platform and two-sided markets." *American Economic Review*, 103(7): 2960–3000.

Lesellier, Max, Hippolyte Boucher, and Gökçe Gökkoca. 2023. "Testing and relaxing distributional assumptions on random coefficients in demand models." *Working Paper.*

Li, Jing. 2023. "Compatibility and investment in the US electric vehicle market." *Working Paper.*

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The market for electric vehicles: indirect network effects and policy design." *Journal of the Association of Environmental and Resource Economists*, 4(1): 89–133.

Metcalfe, R., C. Simpson, A. Schein, and Y. Sun. 2025. "AI in Charge: Large-Scale Experimental Evidence on Electric Vehicle Charging Demand." *Working paper.*

Miravete, Eugenio J, María J Moral, and Jeff Thurk. 2018. "Fuel taxation, emissions policy, and competitive advantage in the diffusion of European diesel automobiles." *The RAND Journal of Economics*, 49(3): 504–540.

Muehlegger, Erich, and David S. Rapson. 2022. "Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California." *Journal of Public Economics*, 216.

Nevo, Aviv. 2001. "Measuring market power in the ready-to-eat cereal industry." *Econometrica*, 69(2): 307–342.

Remmy, Kevin. 2025. "Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles." *Working Paper.*

Reynaert, Mathias. 2020. "Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market." *The Review of Economic Studies*, 88(1): 454–488.

Sinyashin, Alexey. 2021. "Optimal Policies for Differentiated Green Products: Characteristics and Usage of Electric Vehicles." *Working Paper.*

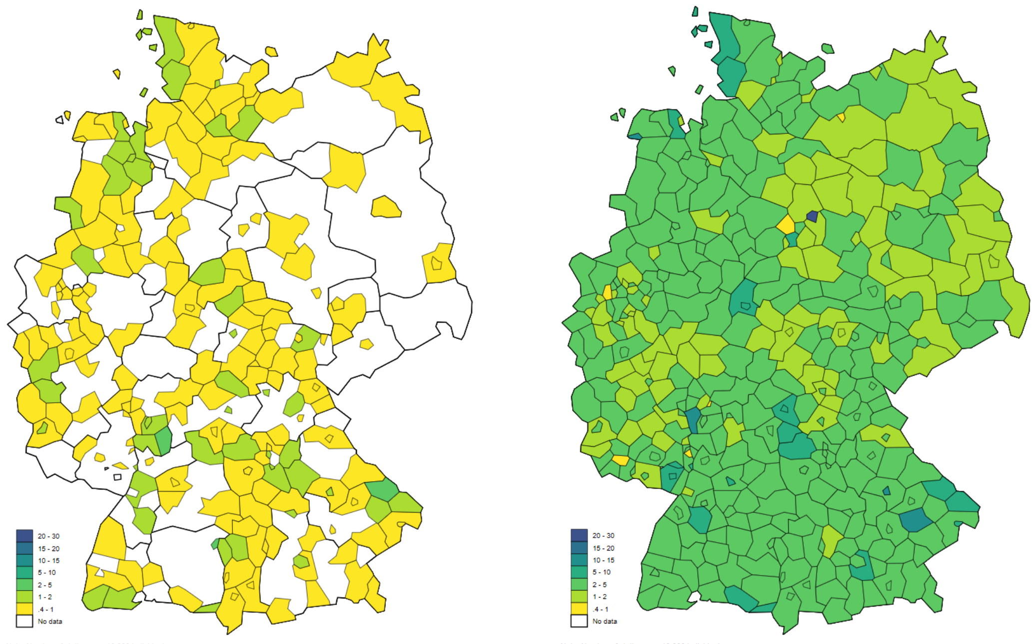
Springel, Katalin. 2021. "Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives." *American Economic Journal: Economic Policy*, 13(4): 393–432.

Xing, Jianwei, Benjamin Leard, and Shanjun Li. 2021. "What does an electric vehicle replace?" *Journal of Environmental Economics and Management*, 107: 102432.

A Appendix

A.1 Additional Figures and Tables

Figure A1: Public chargers per 10k inhabitants by county



2017 2021

Figure A2: Marginal costs by generation type (in €/MWh)

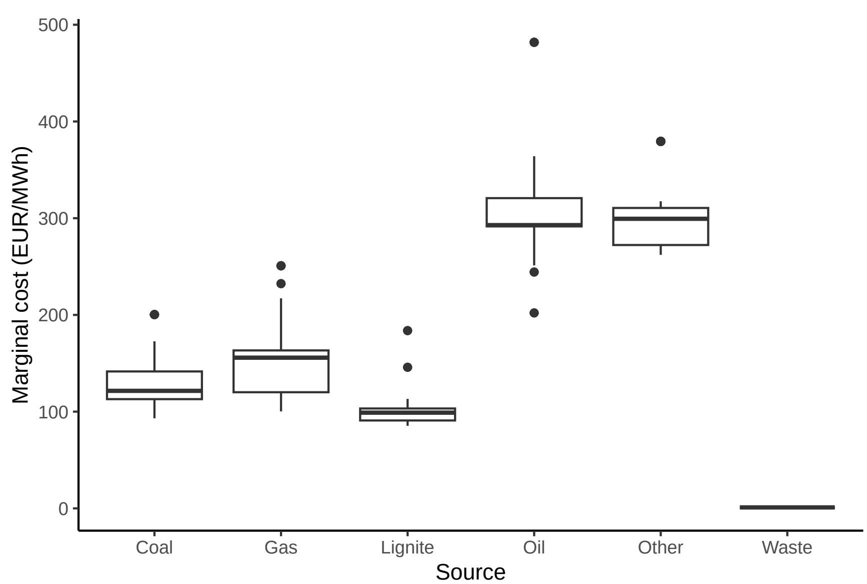
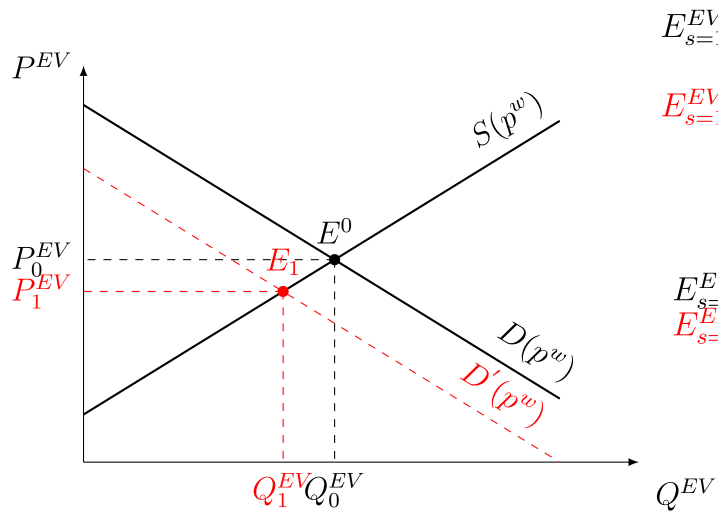
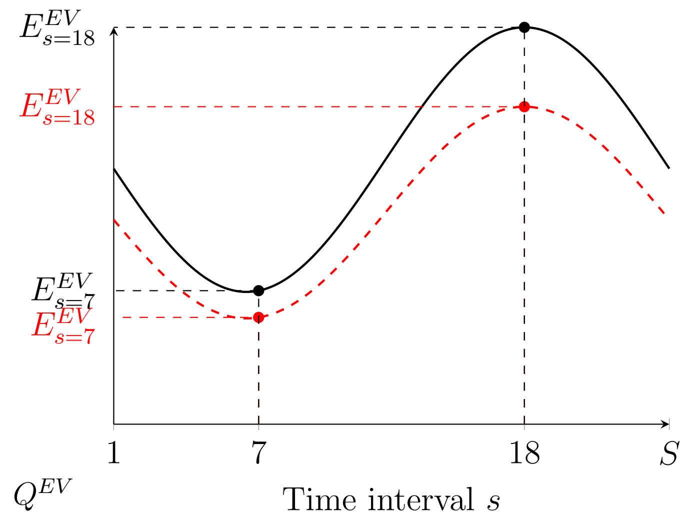


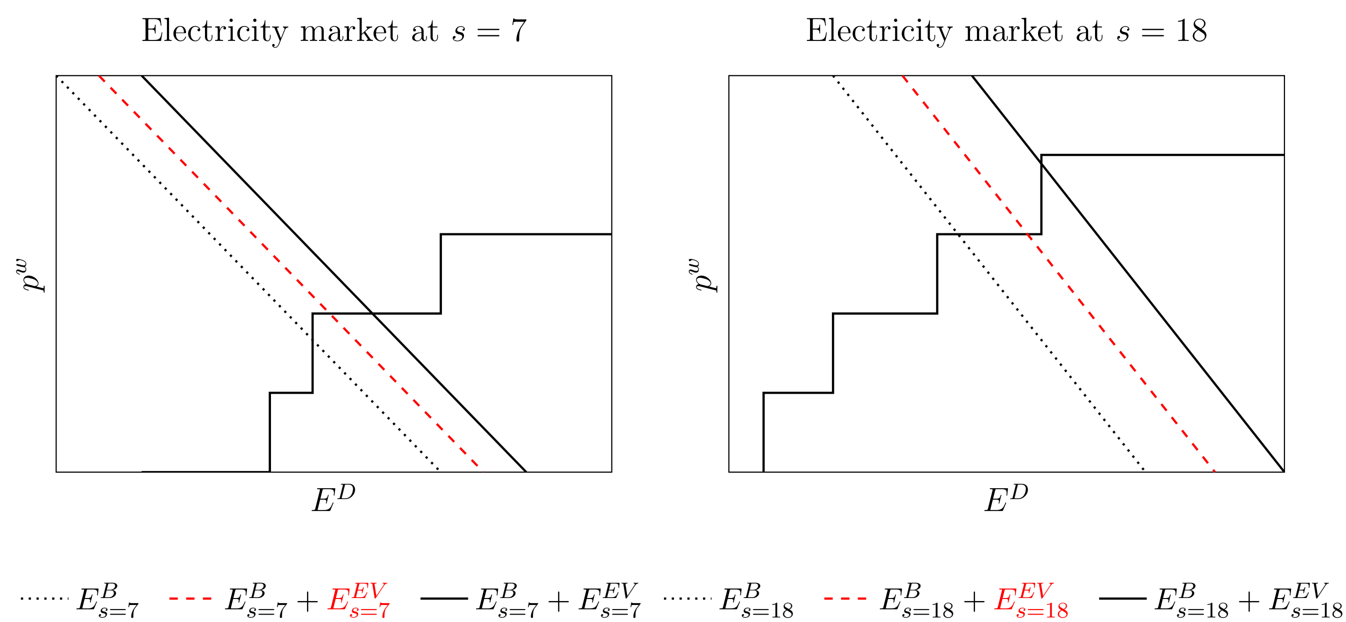
Figure A3: Schematic overview of Complementarity between EV and Electricity Market



(a) Vehicle Demand–supply



(b) EV load profile, $s = 1, \ldots, S$



(d) Electricity market, $s = 18$

(c) Electricity market, $s = 7$

(a) vehicle demand–supply diagram; (b) intra-day EV load shape. (c) low- electricity demand market hour $(s = 7)$ and (d) high-electricity demand hour $(s = 18)$.

Notes: Panel (a) shows vehicle demand–supply intersection, where we show the initial increase in EV demand to E^0 with given electricity prices and the full equilibrium E^1. Panel(b) depicts a intraday EV load curve over S intervals. Panels (c) and (d) map the merit-order supply curve and baseline demand (E^B), baseline and EV electricity demand ($E^B + E^{EV}$, full black line), baseline and EV electricity demand (red dashed) for a low-load hour ($s = 7$) and a high-load hour ($s = 18$), respectively. Panel a, b, c, and d are connected because $p^a = f(p^w), p^h = f(p^w)$ and because E^{EV}_s is a function of the vehicle quantity, which depends on electricity prices.

Table A1: Assumed cost factors and unavailability rates by generation source

Source	Fuel price (in EUR)	Transport cost (in EUR)	Variable cost (in EUR)	Emission Factor	Unavailability rate
Lignite	3.10	0.00	0.40	1.70	13
Coal	16.59	1.25	0.34	1.30	20
Gas	45.16	0.50	0.20	1.25	13
Oil	86.87	0.30	0.28	1.00	15
Other	86.87	0.00	0.21	1.00	15
Waste	0.00	0.00	0.00	1.00	15

Note: We assume a carbon price of EUR 83.66 per t/CO_2.

Table A2: Comparison of Alternate Shadow Peaks

	No EVs	Eq. 1	Eq. 2
Electricity Market:			
Generation (TWh)	459.42	+7.71	+7.71
Weighted price (EUR/mWh)	106.72	+2.21	+2.28
Generation cost (bil EUR)	19.60	+0.77	+0.78
Vehicle Market:			
EV sales (1,000 units)		4,900	4,901
EV price		35,172	35,172
Emissions:			
Grid emissions (mio t)	158.21	+5.41	+5.42
Vehicle emissions (mio t)	61.94	-0.36	-0.35
EVs: gCO2/km		95.00	95.14
Expenditures:			
EV charging (bil EUR)		+1.80	+1.80
Baseline (bil EUR)	49.03	+1.01	+1.05

Note: This Table replicates Table 3 for time-varying prices but shows in Eq. 1 and Eq. 2 the outcomes at the two shadow peaks at which the solution oscillates.

A.2 Adjustment of public charging demand

To obtain total public-charging demand, we rescale observed charging at subsidized stations to account for charging at all public stations. We rely on the Hamburg data—where both subsidized and unsubsidized charging stations are observed—to compute the relevant scaling factors.

Table A3 shows that only about 25–30% of German charging points received subsidies during our sample period. Since our demand and charging model predict charging at all public stations by state, we must adjust observed subsidized-station demand accordingly.

In Hamburg, we observe that subsidized stations experience systematically higher demand per charging point than unsubsidized ones. We therefore compute, by year, the ratio of average charging demand per subsidized to unsubsidized station and assume that this ratio applies uniformly across all German states. Using this ratio and the total number of stations in each state, we scale up the observed charging at subsidized points to obtain total state-level

Table A3: Number of public charging points by year

Year	**Subsidized**	**Total**
2019	7,654	27,016
2020	11,188	37,993
2021	14,945	52,466

public-charging demand, accounting for the higher utilization of subsidized infrastructure.

Finally, because our demand model focuses on *private* BEV sales while the observed charging data include *all* BEVs, we adjust total charging demand downward by the share of privately owned BEVs in each state and year.