Discussion Paper Series – CRC TR 224

Discussion Paper No. 615
Project B 04

Equilibrium Effects in Complementary Markets: Electric Vehicle Adoption and Electricity Pricing

Pascal Heid [1]
Kevin Remmy [2]
Mathias Reynaert [3]

June 2026
(First Version : December 2024)

[1] Pascal Heid, Toulouse School of Economics, University of Toulouse Capitole
[2] Kevin Remmy, University of Mannheim, CEPR, Email: remmy@uni-mannheim.de
[3] Mathias Reynaert, Toulouse School of Economics, University of Toulouse Capitole, CEPR, Email:

Support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 is gratefully acknowledged.

Equilibrium Effects in Complementary Markets: Electric Vehicle Adoption and Electricity Pricing

Pascal Heid, Kevin Remmy and Mathias Reynaert *

May 29, 2026

Abstract

Electric vehicles shift passenger transport from oil to electricity, linking vehicle adoption to hourly power-market conditions. We develop and estimate a joint equilibrium model of German vehicle demand and electricity supply in which driver-specific charging decisions map travel profiles and electricity prices into EV operating costs and load. A 10% EV stock raises wholesale prices by 3.3%, creating sizable cost spillovers on non-EV electricity users, but reduces EV adoption by less than 1%. Time-varying tariffs lower charging costs and shift load to cheaper hours; in equilibrium, EV adoption offsets much of the system-cost relief while redirecting generator profits toward renewables.

Keywords: electric vehicles, electricity markets, charging, complementary markets

JEL codes: L5, L6, L9, Q4, Q5

*Heid: Toulouse School of Economics, University of Toulouse Capitole, Remmy: University of Mannheim, CEPR and CESifo, Reynaert: Toulouse School of Economics, University of Toulouse Capitole and CEPR. We thank Alejandro Mizrahi Cengarle for excellent research assistance, Steve Puller and Shanjun Li for useful discussion, and seminar participants at Toulouse School of Economics, NBER Design and Regulation of Transportation Markets Meeting, University of Mannheim, Mines ParisTech, 1st PSE/ESSEC Workshop: Platforms, Mobility and the Sharing Economy, World Bank, EAERE, UC Berkeley Energy Institute, UC Davis, ULB Energy Workshop, the Salata Institute and MIT CEEPR workshop on the Economics and Policy of Electric Transportation Charging Infrastructure, University of Mannheim, John Hopkins, University College London, Science Po, KU Leuven, Universidad Carlos III, Bocconi University, PSE, Penn Wharton, NHH, University of Bergamo, FGV Rio, VfS, TSEE online seminar, CREST, University of Oldenburg, WU Vienna, ETH Zurich, CEPR Applied IO conference, and JKU Linz. We acknowledge funding by the European Union (ERC, SPACETIME, grant nr. 101077168). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. We acknowledge funding from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program). Support by the German Research Foundation (DFG) through CRC TR 224 (Project B04) is gratefully acknowledged. We gratefully acknowledge funding by the Joachim Herz Foundation.

1 Introduction

Electric vehicles (EVs) are rapidly moving passenger transport from oil to electricity. EVs now account for more than 20% of global new vehicle sales (International Energy Agency, 2025), implying a growing stock of vehicles connected to regional power systems. This shift changes the economics of the complementary energy market for driving. Oil-based fuels are storable and globally traded, while electricity must be balanced continuously and is priced in markets with large intraday variation. As a result, EV adoption and electricity pricing become linked: EV adoption changes the level and timing of electricity demand, while electricity prices affect EV demand through operating costs.

We quantify this two-way feedback between vehicle demand and electricity supply within a structural equilibrium framework using data from Germany. The strength of the interdependence between the two markets is an empirical question: it depends on how wholesale electricity prices respond to EV load and on how EV demand responds to electricity operating costs. The framework combines a discrete-choice model of vehicle demand and pricing with an electricity market model featuring optimal dispatch, imports, ramping costs, and wholesale pricing. The link between the two markets is provided by driver-specific charging cost minimization, which maps driving profiles and electricity price paths into EV operating costs and intraday charging load profiles.

The model allows us to address four central questions. First, how does EV adoption affect electricity prices, emissions, and costs? Second, how strongly do electricity prices feed back into EV adoption through operating costs? Third, how do time-varying tariffs affect charging behavior, EV adoption, and spillovers to other electricity users? Finally, how do these interactions change as carbon prices rise, renewable capacity expands, or electricity demand grows in 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 links individual driving and charging behavior to the timing of electricity demand, allowing EV adoption to affect not only how much electricity is consumed but also when it is consumed. Second, it empirically quantifies the two elasticities that determine the feedback loop: how EV demand responds to electricity operating costs and how wholesale electricity prices respond to EV charging load. Third, it captures how EV-induced price changes spill over to non-EV electricity users and generator profits. This structure allows us to quantify how electricity pricing regimes and market transitions jointly shape EV adoption, electricity prices, emissions, and the distribution of gains and costs from electrification.

Germany provides a particularly informative setting to study these interactions. Battery electric vehicles (BEVs) account for almost 25% of new vehicle sales in 2021, 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 peak-to-trough difference of about 50% of the mean price.[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 its timing. 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 automobile market with manufacturers competing in prices in a Nash–Bertrand game. On the demand side, we extend Berry, Levinsohn and Pakes (1995) by allowing operating costs to vary at the individual–vehicle level with fuel type, driving needs, vehicle efficiency, and access to home charging.[2] Consumers are characterized by travel profiles from the 2017 Mobilität in Deutschland survey, which records driving demand and time at home for more than 60,000 respondents. For each consumer-vehicle pair, these profiles determine fuel or electricity requirements, charging feasibility and location, and expected operating costs.

We estimate the vehicle demand and supply model using German vehicle registrations and vehicle attributes from 2012–2021. We model EV demand to depend on battery range, charging-station density, and EV-specific preferences, while distinguishing the disutility from 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 allowing operating-cost sensitivity to differ not only between internal combustion (ICE) vehicles and EVs, but also between EV owners with and without home-charging access. We address endogenous vehicle prices and indirect network effects between charging stations and vehicle demand following Springel (2021). We rely on instruments for markups, costs, and charging-station entry.

A central empirical challenge is that home charging is not directly observed, even though it is crucial for both EV operating costs and aggregate electricity demand. We discipline the share of EV charging that occurs at home by combining mileage moments with high-frequency public-charging moments. Mileage by fuel type pins down which driving profiles select into EV ownership and thereby the total electricity required by EV adopters. Station-level charging data pin down the amount and timing of electricity supplied through public

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

chargers. The remaining electricity needed to satisfy EV owners' travel demand must be supplied at home. The mileage and public-charging moments discipline the relative disutility of home and public charging and thereby govern how the model allocates EV adopters across home- and public-charging reliance.

We next estimate the electricity market. Driver-specific charging profiles map travel behavior into hourly electricity requirements for each potential EV owner. We combine these profiles with individual EV choice probabilities from the vehicle demand model to construct aggregate EV electricity demand. In the electricity market, hourly dispatch from domestic generators and imports meets inelastic non-vehicle demand and EV charging demand. Thermal generators face convex ramping costs that link production across hours, while imports enter as an additional supply technology with hourly observed marginal costs. We estimate the parameters governing operating-cost adjustments and ramping by matching observed wholesale prices, technology-level generation shares, and output adjustments in 2023, following Elliott (2026). The resulting supply model captures price formation through both the marginal technology in each hour and the intertemporal constraints created by ramping frictions.

Our counterfactuals quantify how the annual vehicle market and the hourly electricity market adjust jointly. We begin from a market configuration in which battery electric vehicles represent 10% of the vehicle fleet, or about 4.8 million cars.[3] At the start of 2025, Germany's BEV stock stood at about 1.65 million, while the government target is 15 million electric cars by 2030. The 10% benchmark is therefore substantially above the current stock but well below the policy target. We also study larger EV stocks, where the same forces become much larger in magnitude.

Under fixed retail electricity prices, the feedback from electricity prices to EV adoption is weak. A 10% EV stock raises weighted wholesale prices by 3.3% and creates sizable cost spillovers on baseline electricity users, but the resulting increase in EV operating costs reduces EV adoption by less than 1%. This finding is important precisely because the feedback does not provide much self-correction: rapid EV adoption without a commensurate expansion of electricity supply can raise costs for non-EV electricity consumers without materially slowing EV diffusion.

Time-varying pricing changes this logic. Fixed retail electricity prices create a well-known inefficiency because consumers do not face the time-varying marginal cost of electricity and therefore have no incentive to shift consumption to low-cost hours (Joskow and Wolfram,

[3]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 for the equilibrium exercise; the final equilibrium stock can deviate from this benchmark depending on the feedback between electricity prices and vehicle adoption.

2012). Recent studies and pilot programs propose exposing EV owners to time-varying prices to reallocate charging toward low-cost periods (e.g., Bailey, Brown, Myers, Shaffer and Wolak, 2024). We extend this insight to a general-equilibrium setting. Holding EV adoption fixed, time-varying prices reduce generation costs, charging expenditures, and the cost spillover on baseline electricity users by shifting charging to lower-cost hours. In the full equilibrium, however, this benefit is substantially attenuated: lower charging costs make EVs more attractive, increasing EV adoption and aggregate charging demand. As a result, time-varying pricing lowers private charging costs and modestly reduces EV emissions intensity, but much of the system-cost relief is offset by the additional adoption it induces.[4]

The equilibrium effects also shape emissions and generator profits. Because the German electricity mix remains carbon-intensive, the emissions savings from EVs are modest in the short run. Time-varying prices slightly lower EV emissions intensity in the baseline counterfactual, but the main electricity-market effect is distributional: EV charging raises electricity-sector profits, and time-varying prices shift more of these gains toward renewable generators and away from fossil generators. This suggests a further channel through which tariff design may affect long-run investment incentives, although we do not model endogenous generation entry.

Finally, time-varying pricing becomes especially important as the electricity sector changes. Higher carbon prices, growth in non-transport electricity demand, and renewable entry all change the relative cost of charging across hours. Under fixed tariffs, EV users cannot respond to this variation, so electricity-market stress can weaken the operating-cost advantage of EVs. Under time-varying prices, consumers shift charging toward lower-cost hours, allowing EV adoption to remain more robust when carbon prices rise, when electricity demand from other sectors expands, and when renewable generation becomes more 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, 2026), and usage costs (Sinyashin, 2021; Bushnell, Muehlegger and Rapson, 2022; Dorsey, Langer and McRae, 2025). Related work studies other margins of the EV transition, including range constraints in usage decisions and global battery-powered vehicle supply chains (Jia Barwick, Li and

[4] 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.

Xia, 2026; Barwick, Kwon, Li and Zahur, 2025; Head, Mayer, Melitz and Yang, 2026); these margins are distinct from our focus on electricity-market feedback. 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 the EV demand and electricity market within a joint equilibrium framework. 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. Empirically, the key measurement challenge is to recover the operating-cost heterogeneity that determines both EV adoption and charging load. We use individual travel data, fuel-specific mileage moments, and high-frequency public-charging moments to discipline this heterogeneity and to map time-varying electricity prices into charging costs and load shifts. 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).

We also contribute to the literature on complementary markets and their interactions. Examples include (Gandal, Kende and Rob, 2000), (Lee, 2013), (Chatterjee, Fan and Mohapatra, 2024), and (Jullien and Bouvard, 2022). Benetton, Compiani and Morse (2023) analyze how rising electricity demand from crypto mining raises 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, and how usage decisions mediate these effects when prices vary over time.

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 equilibrium counterfactual analysis, and Section 7 concludes.

2 Data

2.1 Data sources

We build a comprehensive data set combining sources on car registrations and usage, charging station entry and usage, energy prices, and electricity-market outcomes in Germany. The data define vehicle choice sets and sales moments, assign households driving and charging-access profiles, discipline EV operating costs and the home–public charging split, and estimate the dispatch model mapping EV load into electricity prices, costs, and emissions.

The sources cover different periods because they identify different parts of the model. The vehicle market panel, charging-station counts, retail electricity contracts, public-charging prices, and fuel prices cover 2012–2021. The travel profiles are from the 2017 Mobilität in Deutschland cross-section and are held fixed as representative daily driving patterns. Public-charging transactions cover 2018–2021 nationally, with more detailed records from Hamburg available for 2016–2021. The electricity-market model uses 2023 hourly market outcomes as the dispatch baseline, because 2020–2021 were affected by COVID-19 mobility disruptions and 2022 by the energy-market shock following Russia's invasion of Ukraine.

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 restricting to car owners with nonmissing housing, geography, location, and distance information and complete weekday 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 Agency (Bundesnetzagen-

[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.

tur) 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. NOW GmbH and the National Centre for Charging Infrastructure collect usage information for public charging stations supported by federal entry subsidies. These data record every charging event at public stations that received entry subsidies, including the start and end times, duration, and electricity charged (kWh). The national data therefore cover subsidized public stations rather than the universe of public charging. 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. In estimation, we use 2019 and 2021; we exclude 2018 because data collection starts during that year and 2020 because charging is distorted by COVID-related mobility restrictions. We use the Hamburg records to scale the subsidized-station data to total public-charging demand and then adjust the resulting moments to match the private-owner vehicle sample.

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 fuel-specific driving intensities.

Retail electricity and fuel price data. We use data from multiple sources to measure end-user energy prices.[8] 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. We complement these data with information on plant-level cost factors from the Institute of Energy Economics at the University of Cologne (EWI), as well as hourly production and hourly unavail-

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

[8] Enet provides commercial retail-electricity tariff data, Verivox reports public-charging rates, and Tankerkoenig provides fuel-price data from the German Market Transparency Unit for Fuels.

abilities for plants with installed capacity greater than 100 MW from the European Network of Transmission System Operators for Electricity (ENTSO-E). Hourly system load data are also obtained from ENTSO-E. We use daily data on gas prices (Dutch TTF Natural Gas), hard coal prices (ARGUS-McCloskey API2 CIF ARA thermal coal benchmark), and EU ETS carbon prices (CFI2M6) from investing.com. All electricity market data refer to the year 2023. Appendix Table A1 reports summary statistics for generation plants and Table A2 reports summary statistics on input and CO_2 permit costs.

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.

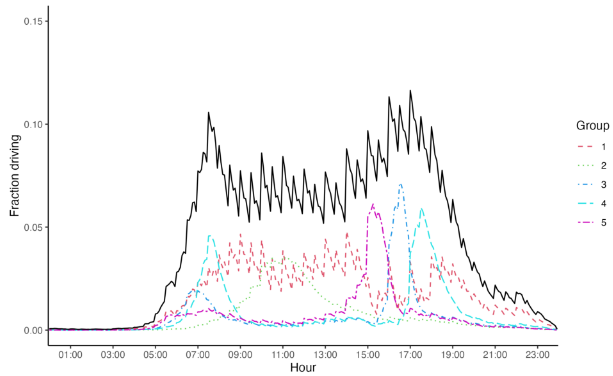
Figure 1a plots, for each driver group, the share of users on the road throughout the day; the black line aggregates these probabilities across all groups. The clusters capture typical usage patterns. Groups 2, 4, and 5 represent commuters leaving in the morning and returning in the afternoon or early 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.

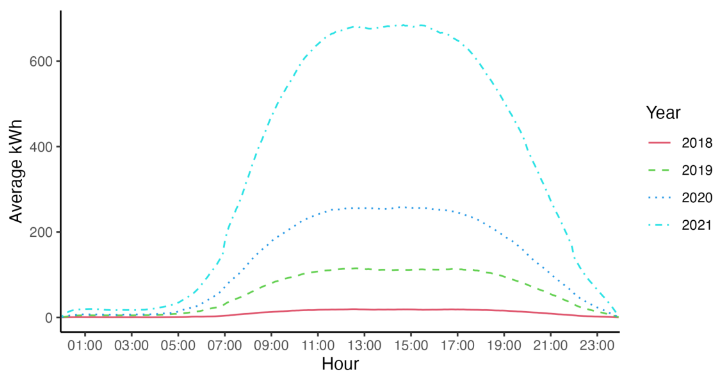
The evolution of EV sales. Figure 2 shows the evolution of vehicle sales by fuel type. As in most EU automobile markets, gasoline and diesel vehicles dominated German sales for decades. Beginning in 2016, alternative powertrains began to gain non-negligible market shares. By 2021, battery electric vehicles (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 do not model their charging behavior, abstracting from the internal trade-off between

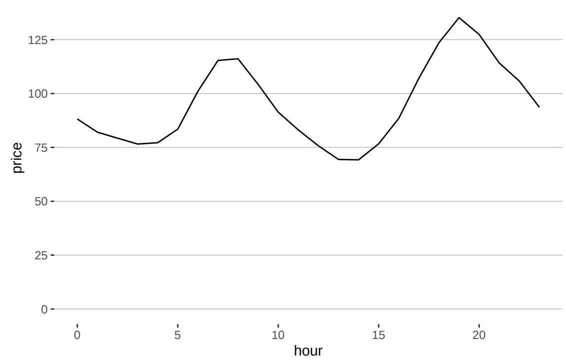
Figure 1: Driving, public charging, and wholesale electricity prices over the day



(a) Driving probability by driver group



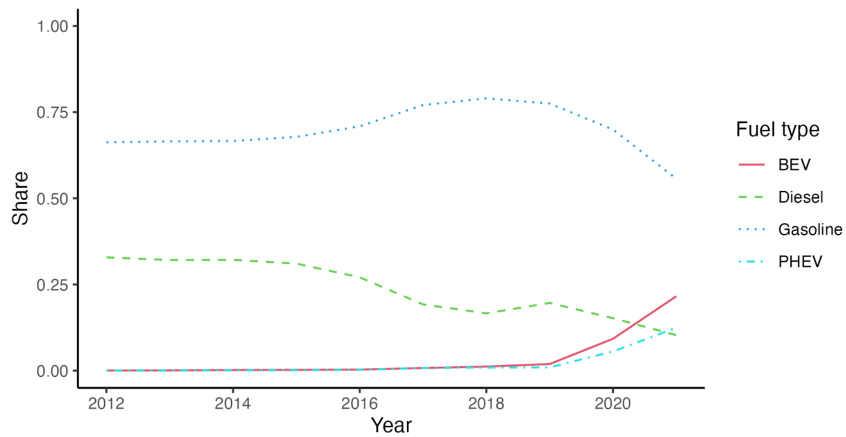
(b) Public charging



(c) Wholesale electricity prices

Note: Panel (a) plots the probability of driving throughout the day for five groups obtained by k-means clustering on travel patterns and distances traveled. The black line aggregates across all groups. Panel (b) shows average hourly electricity charged (kWh) during calendar years 2018–2021 at public stations that received entry subsidies. Panel (c) plots the average hourly wholesale electricity price (EUR/MWh) for calendar year 2023.

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.

charging and refueling. Empirical evidence from Grigolon, Park and Remmy (2026) 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 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 ($\leq$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.

Figure 1b plots the average hourly electricity charged at stations that received investment subsidies. Charging activity is concentrated in daytime hours, with almost no charging overnight, partly reflecting operators' common night-time restrictions. The low observed overnight use motivates the empirical assumption that public charging is unavailable between 11 p.m. and 6 a.m.

Intraday wholesale electricity prices. Figure 1c 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 50% 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 develop an equilibrium model of the new vehicle market that embeds electricity prices as a determinant of expected EV operating costs and hence EV adoption. The model specifies demand and supply in the vehicle market, electricity demand and supply, and a charging technology that maps households' exogenous driving needs into electricity expenditures. Individual charging decisions generate a complementarity between vehicle adoption and electricity prices. We present the vehicle market first, followed by the electricity market and the definition of equilibrium. Charging infrastructure enters households' operating costs through access constraints, but the stock of charging stations is taken as exogenous and does not respond strategically.

3.1 Notation and Timing

Consumers purchase a vehicle that provides services over a lifetime T. We discretize the lifetime into a sequence of representative periods $s = 1, \ldots, S$ capturing a recurring travel pattern. For example, for $T = 15$ years we use repeated two-week sequences at an hourly frequency. We denote such sequences by $(x_s)_{s=1}^S$.

A vehicle market is defined by calendar year t and region g. Regions are state–county-type cells, where county type is metropolitan, urban, mainly rural, or rural following the classification of the Federal Office for Building and Regional Planning.

The endogenous prices in the model are vehicle prices and electricity prices. In each year t, J vehicle models are offered at national prices $(p_j)_{j=1}^J$ chosen once per year by manufacturers; we denote the vector of vehicle prices by $\mathbf{p}_t$. The electricity market clears in each period s of the sequence and is geographically integrated at the national level. In each year t, we distinguish three electricity price sequences: wholesale prices $(p^w_{ts})_{s=1}^S$, regional residential retail prices $(p^h_{tgs})_{s=1}^S$, and regional public-charging prices $(p^a_{tgs})_{s=1}^S$. Retail and charging prices differ across regions because of local markups. Vehicle prices and electricity prices are jointly determined as a fixed point of the model. However, automakers do not model or strategically respond to electricity prices when setting vehicle prices: their Nash-Bertrand problem is the standard vehicle-market problem, evaluated holding electricity-price sequences fixed.

Households are heterogeneous in driving needs and charging access. Each individual i is characterized by an exogenous intraday travel profile $(w_{is})_{s=1}^{S}$, where $w_{is} = (h_{is}, r_{is}, m_{is})$. The indicator h_{is} equals one when the individual is at home, r_{is} equals one when the individual is driving, and m_{is} records kilometers driven when $r_{is} = 1$. Together, these variables determine the individual's location and distance traveled at each interval. Individuals also differ in their ability to charge at home, captured by $l_i \in \{0, 1\}$.

3.2 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 $j \in \chi_i$:

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

where x_{jgt} denotes 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 travel profile w_i using observed fuel prices, vehicle-specific fuel consumption, and the distance traveled over the driving sequence S. The parameter γ^{ICE} measures the marginal disutility of one euro of fuel expense over the sequence.

The EV electricity expense term in (1) is:

$$C_{ijgt}^{EV} \gamma^{EV} = \mathbb{1}\{l_i = 0\} \left[\gamma^a A_{ijgt}^{l_i=0}\right] + \mathbb{1}\{l_i = 1\} \left[\gamma^a A_{ijgt}^{l_i=1} + \gamma^h H_{ijgt}^{l_i=1}\right], \tag{2}$$

where $\gamma^{EV} = (\gamma^a, \gamma^h)$ collects the marginal disutilities of one euro of charging expenditure at public stations and at home. Individuals without access to home charging ($l_i = 0$) rely exclusively on public stations, while individuals with home access ($l_i = 1$) may charge both at home and at stations.

Public-charging expenditures are defined as

$$A_{ijgt}^{l_i} = \sum_{s=1}^{S} e_{ijgts}^{a*} \, p_{tgs}^a,$$

and home-charging expenditures for individuals with home access are

$$H_{ijgt}^{l_i=1} = \sum_{s=1}^{S} e_{ijgts}^{h*} \, p_{tgs}^{h},$$

where e_{ijgts}^{a*} and e_{ijgts}^{h*} denote the optimal charging quantities at public stations and at home implied by individual i's travel profile w_i, vehicle j, and prevailing electricity prices. These quantities are obtained by solving an individual charging problem at both fixed and time-varying electricity prices and are therefore functions of the full intraday price sequences $(p_{tgs}^{a}, p_{tgs}^{h})_{s=1}^{S}$. Appendix Section A.2 gives the formal dynamic program. The battery level is the state variable; driving reduces charge according to kilometers traveled and vehicle-specific electricity consumption, charging is possible only when the vehicle is not being driven, and the battery must remain between zero and vehicle-specific capacity in every interval. Individuals without home access can charge only at public stations, whereas individuals with home access face the home tariff when at home and the public tariff otherwise. If a travel profile cannot be completed by vehicle j without violating the battery constraints, that vehicle is excluded from the individual's choice set χ_i. This approach contrasts with the existing EV literature, which typically treats charging costs as reduced-form functions of vehicle characteristics rather than as the outcome of an explicit charging decision problem (e.g., Springel, 2021; Remmy, 2026).

In total, three parameters capture the disutility from operating expenses: γ^{ICE} and $\gamma^{EV} = (\gamma^a, \gamma^h)$. Under full capitalization, one euro of discounted operating cost would enter utility in the same way as one euro of the vehicle purchase price, so that these parameters translate per-sequence expenses into their net present value over the vehicle lifetime. A large literature, however, documents that consumers undervalue future fuel costs relative to upfront vehicle prices (Hausman, 1979; Busse, Knittel and Zettelmeyer, 2013; Allcott and Wozny, 2014; Grigolon, Reynaert and Verboven, 2018). We therefore estimate operating-cost valuation rather than impose full capitalization, and additionally allow the valuation of electricity costs to differ from that of fuel costs. Electricity prices may be less salient, and refueling time and convenience costs may differ between liquid fuels and electricity. Consistent with this distinction, Bushnell, Muehlegger and Rapson (2022) provide evidence that consumers value fuel and electricity expenses differently. Our specification further distinguishes between residential electricity expenses (γ^h) and public-charging expenses (γ^a), reflecting potentially higher inconvenience or congestion costs associated with charging at public stations relative to charging at home.

Individual choice probabilities $\sigma_{ijgt}(\cdot)$ follow from the Type-I extreme value assumption on ϵ_{ijgt}. Aggregating over households yields vehicle sales

$$q_{jgt} = \iint L_{gt}\, \sigma_{ijgt}\big(\mathbf{p}_t, (p^a_{tgs})_{s=1}^S, (p^h_{tgs})_{s=1}^S, w_i, \nu_i\big)\ dF_\nu(\nu_i)\, dF^g_w(w_i), \tag{3}$$

where $\sigma_{ijgt} = 0$ for $j \notin \chi_i$ and L_{gt} denotes the potential market size.[10] The vector ν_i captures unobserved preference heterogeneity.

Vehicle demand depends on three endogenous price objects: vehicle prices $\mathbf{p}_t$, residential electricity prices $(p^h_{tgs})_{s=1}^S$, and public-charging prices $(p^a_{tgs})_{s=1}^S$. Electricity price sequences affect EV adoption through the operating-cost terms in (2).

Vehicle Supply Let J_f denote the set of vehicles produced by manufacturer f. Most manufacturers produce ICE and EV vehicles. A firm's annual profits are:

$$\Pi_{ft}(\boldsymbol{p}) = \sum_g \sum_{j \in J_f} [p_{jt} + \lambda_{jt} - mc_{jt}]\, q_{jgt}(\boldsymbol{p}, (p^h_s)_{s=1}^S, (p^a_s)_{s=1}^S), \tag{4}$$

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 vehicle prices. Firms take the electricity-price sequences as fixed when setting annual vehicle prices; in particular, they do not account for how a marginal change in vehicle prices would alter electricity 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 $D_{jht} = -\sum_g \frac{\partial q_{hgt}(\boldsymbol{p}, (p^h)_{s=1}^S, (p^a)_{s=1}^S)}{\partial p_{jt}}$, where the derivative holds electricity prices fixed. Then, the vector of first-order conditions of the firms' maximization problem is:

$$\boldsymbol{p} + \boldsymbol{\lambda} - (\Omega \odot D(\boldsymbol{p}))^{-1}\boldsymbol{q} - \boldsymbol{mc} = 0, \tag{5}$$

where $\boldsymbol{q} = \sum_g q_{jgt}$ is the vector of vehicle quantities, and $\odot$ denotes the Hadamard (element-wise) product. Electricity prices affect consumer demand through EV operating costs, but they are not a strategic object in the automakers' pricing problem.

[10] The travel survey reports fractions z_i of vehicle owners with profile w_i. These are conditional on vehicle purchase, while (3) is defined over the full population. Following Grigolon, Reynaert and Verboven (2018), we recover population shares π_i via $\pi_i = z_i\big(Q/(L\sum_j \sigma_{ij})\big)$, where $Q = \sum_j q_j$ and market subscripts are omitted for clarity. This transformation is applied when integrating over F^g_w.

3.3 Electricity market model

Electricity demand We model electricity demand as the sum of an inelastic baseline component E_{ts}^{B}, capturing non-EV consumption, and EV-induced charging demand:

$$E_{ts}^{D} = E_{ts}^{B} + E_{ts}^{EV}, \tag{6}$$

for each interval $s = 1, \ldots, S$. The term E_{ts}^{EV} is obtained by aggregating optimal charging quantities across households and vehicles implied by the vehicle demand system and the charging problem. Together, $(E_{ts}^{D})_{s=1}^{S}$ define the intraday electricity load profile.

Changes in vehicle prices, such as those induced by purchase subsidies, affect electricity demand through their impact on EV adoption in (3). Electricity prices affect EV adoption through expected operating costs and shape the intraday load profile through the optimal charging behavior of EV adopters.

Electricity supply. Electricity is supplied by units $u = 1, \ldots, U$, where the set of units includes domestic generators and an import technology. Let e_{uts} denote output from unit u in interval s, subject to the capacity constraint $0 \leq e_{uts} \leq \bar{e}_{uts}$. Available capacity $\bar{e}_{uts}$ varies with realized wind and solar conditions for renewable units, reflects available conventional capacity for thermal units, and captures the quantity that can be imported in interval s. Imports enter the market as an additional source of supply with observed hourly marginal cost.[11]

Following Elliott (2026), thermal production costs combine variable operating costs with convex ramp-up costs. For a thermal unit, the cost of producing e_{uts} in interval s given output $e_{ut,s-1}$ in the previous interval is

$$C_{uts}(e_{uts}, e_{ut,s-1}) = mc_{uts} e_{uts} + \frac{r_u}{2} \left(\max\{e_{uts} - e_{ut,s-1}, 0\}\right)^2, \tag{7}$$

where mc_{uts} denotes the unit's marginal operating cost and r_u is its ramping-cost parameter. Renewable units and imports have linear costs $C_{uts}(e_{uts}) = mc_{uts} e_{uts}$, with $mc_{uts} = 0$ for renewable generation and mc_{uts} equal to the observed import price for the import technology.

Because ramping costs couple adjacent intervals, dispatch is determined over the full sequence rather than hour by hour. In each year t, the system operator solves

$$\min_{\{e_{uts}\}_{u,s}} \sum_{s=1}^{S} \sum_{u=1}^{U} C_{uts}(e_{uts}, e_{ut,s-1}) \tag{8}$$

[11] Because imports are observed only at the country level, rather than at the level of individual foreign generating plants, we proxy the marginal cost of imported electricity with the observed hourly wholesale price in the exporting country.

subject to

$$\sum_{u=1}^{U} e_{uts} = E_{ts}^{D} \quad \forall s$$

and

$$0 \leq e_{uts} \leq \bar{e}_{uts} \quad \forall u, s.$$

The wholesale equilibrium price p_{ts}^{w} is the Lagrange multiplier on the market-clearing constraint in interval s. When $r_u = 0$ for all thermal units, (8) collapses to a standard static merit-order dispatch.

Following Elliott (2026), we estimate the ramping costs by matching model-implied and observed wholesale prices, technology-level generation shares, and output adjustments across intervals. This approach allows the supply side to capture both the level of operating costs and the persistence in generation implied by ramping frictions.

We assume retailers and public-charging providers add fixed region-specific markups to wholesale prices. Under fixed-price contracts,

$$p_{tg}^{a} = \mu_g^{a} + \bar{p}_t^{w} \quad \text{and} \quad p_{tg}^{h} = \mu_g^{h} + \bar{p}_t^{w},$$

where

$$\bar{p}_t^{w} = \frac{\sum_{s=1}^{S} p_{ts}^{w} E_{ts}^{D}}{\sum_{s=1}^{S} E_{ts}^{D}}$$

is the load-weighted average wholesale price in year t. For any charging channel exposed to time-varying wholesale prices, prices satisfy

$$p_{tgs}^{a} = \mu_g^{a} + p_{ts}^{w} \quad \text{and} \quad p_{tgs}^{h} = \mu_g^{h} + p_{ts}^{w}.$$

In the counterfactuals below, we apply this time-varying pass-through to home charging.

3.4 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 $(p_{ts}^{w})_{s=1}^{S}$ such that:

1. For each individual-vehicle-market combination, charging quantities $(e_{ijgts}^{h*}, e_{ijgts}^{a*})_{s=1}^{S}$ solve the charging problem in Appendix Section A.2 at the prevailing residential and public-charging price sequences. These quantities determine the electricity expenditure terms $A_{ijgt}^{l_i=0}$, $A_{ijgt}^{l_i=1}$, and $H_{ijgt}^{l_i=1}$.

2. Vehicle demand satisfies (3), and firms set vehicle prices $\boldsymbol{p}$ according to the first-order

conditions in (5), taking electricity prices as fixed in the pricing problem. The resulting vehicle market equilibrium implies an EV-induced electricity load profile E^{EV}_{ts}.

3. Electricity demand is given by (6), electricity supply solves the dispatch problem in (8), and the market clears in every interval, $\sum_{u=1}^{U} e_{uts} = E^D_{ts}$, yielding equilibrium prices $p^w_{ts}, p^a_{tgs}, p^h_{tgs}$.

To build intuition about the interaction between the vehicle and electricity markets, consider the introduction of EVs into consumers' choice sets at prevailing wholesale, residential, and public-charging electricity prices. Given these prices, a subset of consumers adopts EVs based on the expected operating costs implied by their exogenous travel profiles $(w_{is})_{s=1}^{S}$. Conditional on adoption, EV owners generate heterogeneous intraday electricity load profiles through their charging choices. Appendix Figure A3 provides a schematic illustration of this mechanism.

Aggregating across EV adopters yields the EV-specific load sequence $(E^{EV}_{ts})_{s=1}^{S}$, which raises total electricity demand from E^B_{ts} to $E^B_{ts} + E^{EV}_{ts}$. The increase in demand changes the optimal dispatch across domestic generators and imports and raises wholesale prices p^w. These prices pass through to residential and public-charging prices, p^h and p^a, increasing EV operating costs and feeding back into adoption decisions. Appendix Figure A3 plots the resulting fixed-point between EV adoption, dispatch, and electricity prices in red.

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

4.1 Demand Estimation

This section describes the estimation of the vehicle demand model and the identification of the parameters governing the elasticity of EV adoption with respect to electricity prices. We estimate the demand model using regional market shares and micro-moments that allow us to differentiate between the amount of home and public charging.

The estimation faces five main challenges. First, we must construct operating-cost objects that map electricity prices and travel needs into operating costs. Second, vehicle prices are endogenous because manufacturers observe product attributes unobserved to the econometrician. Third, charging-station density d_{gt} is potentially endogenous due to indirect network effects from EV adoption. Fourth, we must identify the operating-cost valuation parameters γ^{ICE} and $\gamma^{EV} = (\gamma^a, \gamma^h)$ that govern the sensitivity of adoption to fuel and electricity expenses. Fifth, we must recover which travel-profile types select into EV ownership and how these owners rely on home and public charging to link vehicle demand to the electricity market.

Operating Costs For ICE vehicles, fuel costs C_{ijgt}^{ICE} are obtained by multiplying regional fuel prices by the fuel required to cover the kilometers traveled for each individual–vehicle combination. For EVs, we compute public- and home-charging expenditures $A_{ijgt}^{l_i=0}$, $A_{ijgt}^{l_i=1}$, and $H_{ijgt}^{l_i=1}$, and determine the feasible choice set χ_{it} in each calendar year t. These objects are constructed for each individual–vehicle–region–year combination, yielding more than eleven million EV electricity-cost observations.

Individual travel profiles $(w_{is})_{s=1}^{S}$ are taken from the car-usage survey. We restrict the sample to weekdays and to car owners. Each observed daily profile is repeated to form a horizon of $S = 14$ days. The survey identifies the individual's region g. The vehicle registration data provide battery capacity and electricity consumption per kilometer for each EV model j. We assume a uniform charging power of 11 kW, consistent with Level-2 chargers, which account for the large majority of public chargers installed prior to 2021.

We use data on residential and public-charging electricity rates to construct average annual regional prices p_{tg}^h and p_{tg}^a. Public charging is uniformly more expensive than home charging. In Germany, in our sample period, residential electricity contracts are flat-rate and charging-station prices do not vary intraday, so observed prices are constant over the sequence S. Our counterfactual analysis introduces intraday price variation through time-varying tariffs.

For each individual–vehicle–region combination, we compute charging feasibility and operating costs. We first test if individuals with home-charging access can rely exclusively on home charging. If home charging alone is insufficient for the driving profile, we allow a combination of home and public charging, restricting public charging to non-driving periods outside nighttime hours (11 p.m.–6 a.m.), consistent with observed station usage. If total charging capacity remains insufficient, the EV is excluded from the individual's choice set χ_{it}.

Individuals without home access rely exclusively on public charging, subject to the same nighttime restriction. EVs that cannot satisfy the individual's driving needs under these constraints are excluded from the choice set. Energy-efficient vehicles and models with larger batteries are therefore more likely to belong to χ_{it}, particularly for high-mileage individuals.

Identifying home charging Home charging is not directly observed in our data. We discipline its aggregate level indirectly through an accounting restriction. Conditional on the model-implied composition and scale of EV sales, the mileage moments discipline total distance driven by EV owners. Combining this distance with vehicle-specific electricity consumption disciplines total EV electricity demand. The public-charging moments discipline the component of this demand supplied at charging stations. The remaining electricity demand must therefore be supplied through home charging.

This restriction is informative about the relative disutility of home and public charging. If the model assigns too many high-mileage EV buyers to public charging, it overpredicts observed station demand. If it assigns too few high-mileage consumers to EVs, it fails to match EV mileage. The estimates therefore require enough high-mileage EV adoption among households with home access, while limiting adoption among households that rely primarily on public charging. This joint restriction disciplines γ^h and γ^a.

The aggregate level of home charging is distinct from its intraday timing. Since historical residential tariffs are flat within the day, home-charging timing under fixed prices is not identified from price variation; we therefore impose the behavioral assumption that drivers plug in upon returning home after their last trip and charge until the battery is full. In counterfactuals with time-varying tariffs, by contrast, home-charging timing is determined by the cost-minimizing charging problem described in Appendix Section A.2.

GMM Objective Function We use three classes of moments. First, standard BLP-style moments $E[\xi_{jgt}z_{jgt}] = 0$ based on an instrument set z_{jgt} identify price and product-characteristic coefficients. Second, we match state-level 5-minute public-charging loads using moments $E[\eta_{Gts}] = 0$, which discipline the mapping from travel profiles to public-charging demand. Third, we use mileage moments for EV, gasoline, and diesel vehicles, $E[\eta_t^{m,EV}] = 0$, $E[\eta_t^{m,gasoline}] = 0$, and $E[\eta_t^{m,diesel}] = 0$, which identify the selection of driving profiles into vehicle types.

Let

$$\Phi = \left(\Phi^{BLP}, \Phi^{charge}, \Phi^{m,EV}, \Phi^{m,gasoline}, \Phi^{m,diesel}\right)$$

denote the stacked sample analogs of these moments, and let $\gamma = (\gamma^{ICE}, \gamma^a, \gamma^h)$ collect the nonlinear operating-cost parameters. We estimate γ by minimizing the GMM objective

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

where W is a consistent estimator of the inverse asymptotic variance–covariance matrix. The weighting matrix is block diagonal because we match three distinct samples: vehicle registrations, public charging data, and insurance mileage records. We minimize the objective function with respect to the nonlinear parameters γ.[12]

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 households retain vehicles for seven years and therefore set L_{gt} equal to the total number of cars owned in gt divided by seven.[13]

We model the indirect utility in (1) 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 for the "most powerful" instruments of Lesellier, Boucher and Gökkoca (2023). Specifically, we add the quartiles of $A^{l_i=0}_{ijgt}$, $A^{l_i=1}_{ijgt}$, $H^{l_i=1}_{ijgt}$, and fuel costs–denoted, for example, $Q_{0.25}(A^{l_i=0}_{jgt})$–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^a_{Gts} denote the observed aggregate station charging in state G from the

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

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

stock of EVs at time t and interval s. We impose:

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

Here e^{*a}_{ijgks} 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 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.[14] 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 as described in Appendix A.3.

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:

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

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

4.2 Electricity Market Estimation

We estimate the electricity market model on German hourly data for 2023 using the ramping specification introduced in Section 3. For each hour, realized electricity demand and renewable output determine residual demand for conventional generation. The production

[14] 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.

data distinguish renewable units, imports, generic thermal technologies, and named thermal plants.[15] Renewable generation is treated as must-take and priced at zero marginal cost. Imports are included with observed hourly import prices. We treat the generic coal, lignite, and gas technologies as non-strategic residual suppliers and pre-dispatch them at their observed hourly production. The optimization step is therefore restricted to named coal, named lignite, and named gas plants, where gas treats open and combined cycle units as a single technology group for estimation.

Let $\mathcal{K} = \{\text{coal}, \text{lignite}, \text{gas}\}$, and let $\kappa(u) \in \mathcal{K}$ denote generator u's technology. For each named thermal generator u, hourly production solves the quadratic dispatch problem in (8). We construct the baseline marginal operating cost for each generator and hour τ from fuel costs and emissions costs. Let EUA denote the EU Emissions Trading System allowance price, measured in euros per tonne of CO_2. Then:

$$mc^0_{u\tau} = \frac{\text{fuel price}_{u\tau}}{\text{efficiency}_u} + \text{EUA}_\tau \times \frac{\text{emissions factor}_u}{\text{efficiency}_u}.$$

The data report generator-specific efficiency rates, and Appendix Table A2 details the remaining inputs used to construct $mc^0_{u\tau}$. We parameterize operating costs as:

$$C_{u\tau}(q_{u\tau}, q_{u,\tau-1}) = \left(mc^0_{u\tau} + \nu_{\kappa(u)}\right) q_{u\tau} + \frac{1}{2}\frac{r_{\kappa(u)}}{K_u}\left(\max\{q_{u\tau} - q_{u,\tau-1}, 0\}\right)^2,$$

where K_u denotes the unit's capacity, ν_κ are technology-specific operating and maintenance costs, and r_κ is a technology-specific ramping parameter. Dividing r_κ by capacity allows units within a technology to share a common technology-level ramping parameter while preserving the idea that ramping is easier for larger plants. The six parameters to be estimated are $(r_{\text{coal}}, r_{\text{lignite}}, r_{\text{gas}}, \nu_{\text{coal}}, \nu_{\text{lignite}}, \nu_{\text{gas}})$.

The hourly market-clearing algorithm has two steps. In the first step, all technologies for which we do not estimate ramping are dispatched. Renewable and other must-run generation are injected at observed availability, and the generic coal, lignite, and gas technologies together with imports are then called in merit order up to their observed hourly quantities. This step lowers residual demand but does not eliminate it in most hours. In the second step, the remaining demand is allocated across the named coal, lignite, and gas plants by solving the ramping problem over the full sample path, taking lagged production as the initial condition. Wholesale prices are the shadow values on the hourly market-clearing constraints. The ramping parameters are therefore identified from the main body of hourly observations

[15] Production data are observed only for plants with at least 100 MW of installed capacity. These correspond to the named thermal plants in our data. We aggregate all smaller plants into generic units by energy source.

in which the large thermal units are active, rather than from a narrow set of exceptional peak hours. We assume competitive bidding and do not model transmission constraints.

We estimate the six parameters by simulated method of moments, following the logic of Elliott (2026). To reduce the computational burden, we simulate 100 draws of contiguous 55-hour sequences from the 2023 data. For each draw we feed observed demand, renewable availability, import prices, generic production, and lagged output in the initial hour into the dispatch problem, solve for equilibrium production and prices, and compute the corresponding simulated moments.

The estimator matches seven moments. The first is a price moment matching the average wholesale price. The next three moments are technology shares,

$$\text{share}_{\kappa\tau} = \frac{\sum_{u:\kappa(u)=\kappa} q_{u\tau}}{\sum_{u\in\mathcal{T}} q_{u\tau}},$$

where $\mathcal{T}$ denotes the set of named thermal plants, $\kappa \in \mathcal{K} = \{\text{coal}, \text{lignite}, \text{gas}\}$ indexes technologies, $\kappa(u)$ denotes the technology of plant u, and τ indexes hours. The final three moments are technology-level ramping moments,

$$\text{ramp}_{\kappa\tau} = \frac{1}{N_\kappa} \sum_{u:\kappa(u)=\kappa} \max\left\{0, \frac{q_{u\tau} - q_{u,\tau-1}}{K_u}\right\} \times 100,$$

where N_κ is the number of named thermal plants of technology κ. This moment measures the average positive output adjustment within each technology as a percentage of capacity. Let m^{data} denote the vector of empirical moments and $m(\theta)$ the simulated counterpart for parameter vector θ. We choose $\hat{\theta}$ to minimize

$$\hat{\theta} = \arg\min_{\theta} \left[m(\theta) - m^{data}\right]' W \left[m(\theta) - m^{data}\right],$$

where W is the inverse sample variance–covariance matrix of the hourly moment vector. For the time-of-day price moments, we use the corresponding within-window variances; for the remaining moments, W uses the full covariance block across prices, shares, and ramping moments.

Appendix Figure A2 provides a static illustration of the underlying cost heterogeneity in the German generation fleet. In the empirical model, renewable output, imports, and generic thermal production are taken hour by hour from the data, while named thermal units are dispatched jointly across hours through the ramping problem. We restrict estimation to hours with non-negative wholesale prices, where residual-demand reallocation across conventional technologies is most informative about marginal costs and ramping behavior.

5 Results

5.1 Fuel and Electricity Expenses

Table 1 summarizes the operating-cost objects that enter the demand model before equilibrium choice probabilities are applied. The averages are unconditional across travel profile–vehicle–region combinations and show the scale and dispersion of the fuel and electricity expenses that generate heterogeneity in the indirect utilities. The demand estimates below then combine these cost primitives with preferences and choice probabilities to produce the conditional operating expenses and charging patterns of selected vehicle owners. The same charging-cost calculations also determine EV feasibility. BEVs can satisfy almost all weekly travel profiles under our charging constraints: only 1% of sampled individuals have at least one BEV excluded from their choice set.

For combustion vehicles, the average daily fuel costs are €2.7 with a standard deviation of 3.9. This variation reflects 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 but not acceleration. 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, 2026; 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 operating-cost parameters are γ^h, γ^a, and γ^{ICE}. Table 2 first shows estimates based

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.

on the aggregate sales moments Φ^{BLP} and then shows results when we include all moments, including those that match station charging and mileage by fuel type (EV, gasoline, diesel). The lower panel translates the operating-cost coefficients into valuations relative to the vehicle purchase price coefficient. These ratios measure how one euro of discounted operating expenses enters utility relative to one euro of upfront vehicle price. A value of one corresponds to full capitalization. In the full specification, the implied valuation is 1.17 for combustion-fuel expenses, 1.63 for home-charging expenses, and 3.61 for public-charging expenses. Thus consumers treat public-charging expenses as especially costly, consistent with public charging bundling monetary costs with inconvenience, search, and reliability concerns. Home-charging expenses are also valued above fuel expenses, although the gap is much smaller than for public charging.

The moments on public charging and mileages by fuel type 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 predicts that 29% of BEV buyers lack home-charging access and that these public-charging buyers drive 13.1 km per day on average. Once we add moments matching public charging and mileage, the estimated disutility from public charging rises, reducing the predicted share of BEV buyers without home access to 24%. Their average mileage remains nearly unchanged, at 12.9 km per day. The main adjustment instead occurs among households with home access: their share among BEV buyers rises from 71% to 76%, and their average daily mileage increases from 25.3 to 33.3 km.

Table 2: Demand Estimates

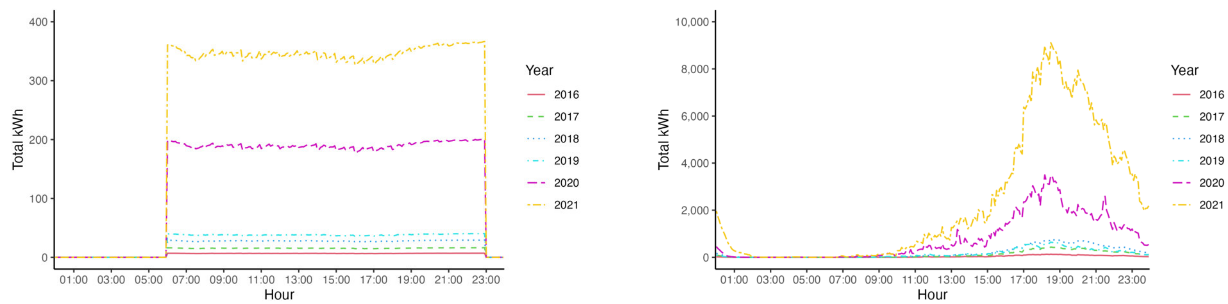
	Logit OLS		**Only Φ^{BLP}**		Φ	
Variable	Coeff.	St.Err.	Coeff.	St.Err.	Coeff.	St.Err.
Taste parameters (α, β):						
Price	-0.022	0.001	-0.067	0.002	-0.068	0.003
Range	0.002	0.000	0.002	0.000	0.002	0.000
Charging station density	0.578	0.020	0.707	0.032	0.671	0.044
Volume	0.043	0.005	0.162	0.007	0.173	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^{BLP} aggregate market-share moments with differentiation instruments, vehicle cost shifters, "most powerful" usage-cost instruments, and charging-station cost shifters; (ii) Φ^{charge} state-level moments matching observed public charging at five-minute intervals; and (iii) Φ^{m} mileage moments matching average mileage by fuel type from insurance data.

The micro-moments therefore discipline selection by reallocating high-mileage EV ownership toward households that can rely primarily on home charging, while limiting EV adoption among households dependent on public charging.

The charging model and demand estimation results together allow us to predict home and public charging throughout the day, plotted in Figure 3. The public charging (left panel) closely matches the observed curve in Figure 1b, as this is targeted by the micro-moment Φ^{charge}. The only noticeable difference appears in the early morning and reflects our assumption that no station charging occurs between 11 p.m. and 6 a.m.

Figure 3: 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, the charging feasibility constraints, and the fixed-price home-charging timing assumption.

The right panel of Figure 3 shows model-predicted home charging under the observed flat residential electricity tariffs. Because these tariffs provide no within-day price incentives, we impose the behavioral assumption that drivers plug in and begin charging immediately upon arriving home after their last trip. This assumption concentrates home charging in the early evening, with a pronounced peak between 5 p.m. and 7 p.m. and little charging later at night, since most EVs need less than one hour of charging to recover daily energy use. In the counterfactuals below, where tariffs vary within the day, this timing is no longer imposed: households choose charging times by solving the cost-minimization problem under the time-varying electricity prices.

5.3 Electricity Market Results

Table 3 reports the estimates for the O&M and ramp-up cost parameters. We estimate a slightly negative O&M cost parameter for coal plants, but the estimate is statistically indistinguishable from zero. The small negative estimate therefore indicates that, conditional on

Table 3: Electricity Production Cost Estimates

	Coal	Lignite	Gas
Estimates			
O&M $\hat{\nu}_\kappa$	-0.801	5.519	4.034
	(0.878)	(0.979)	(0.958)
Ramping cost $\hat{r}_\kappa$	1942.4		1842.1
	(856.2)		(961.5)
Moments			
		Data	Simulation
Avg. price (EUR/MWh)		99.02	102.80
Fraction produced by			
Coal		22.9%	23.1%
Lignite		54.9%	54.8%
Gas		22.1%	22.1%
Avg. increase in capacity utilization for			
Coal		0.94%	1.30%
Lignite		1.15%	1.61%
Gas		0.77%	1.06%
Num. obs.		8,459	
Num. simulation draws		100 times 55 hours	

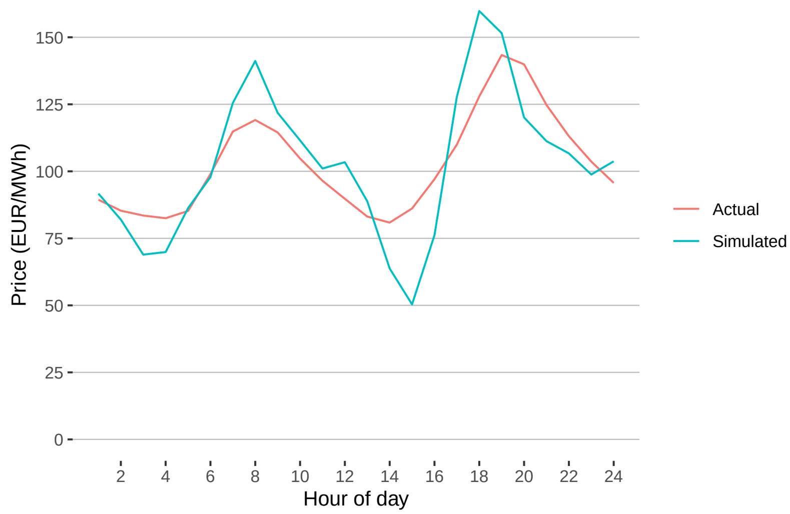
Notes: The weighting matrix is the inverse of the sample covariance matrix of the moments. Coal and Lignite share a common ramping cost parameter $\hat{r}_{\text{coal,lig}}$.

other cost components and constraints, the simulated dispatch fits observed coal generation best when the residual coal O&M component is close to zero. For lignite and gas plants, the residual O&M cost estimate is small and positive, as expected. We estimate a common ramp-up cost parameter for coal and lignite plants, which we estimate to be slightly higher than the one for gas plants.

These estimates matter for the EV counterfactuals because additional charging demand affects the electricity market through both the level and the timing of load. In hours with abundant renewable generation, incremental EV charging can be met with little additional fossil generation. In hours when residual demand is positive, however, additional load is supplied by marginal thermal units. Which technology is marginal depends on the position of residual demand on the merit order and on ramping constraints that limit how quickly coal, lignite, and gas plants can adjust output. The ramping-cost estimates therefore govern the extent to which concentrated EV charging peaks raise wholesale prices and emissions relative to smoother charging profiles. Combining the demand model's predicted charging profiles with the dispatch model allows us to map vehicle adoption into hourly electricity production, prices, and emissions.

Figure 4 compares observed and model-predicted average intraday spot prices. Since time-of-day price moments enter the estimation, the figure should be interpreted as an in-

Figure 4: Comparison of observed and predicted wholesale prices



Intra-day prices

Note: The figure plots observed and model-predicted intraday electricity prices.

sample assessment of model fit. The model reproduces the main intraday pattern in wholesale prices, although the predicted curve is slightly more pronounced than the observed curve.

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, higher carbon prices, and broader growth in electricity demand.

6.1 Counterfactual Setup

The demand model predicts annual EV sales (flows), while the electricity market responds to the stock of EVs on the road. Let Q^{EV} denote the annual EV sales implied by the vehicle market in a given scenario. We map this flow into the corresponding EV stock according to

$$N^{EV} = \Gamma Q^{EV},$$

where we calibrate $\Gamma = 27.51$ such that 2021 EV sales imply a stock of 4.8 million EVs, or 10% of Germany's roughly 48 million registered vehicles.[16] 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 therefore interpret a 10% EV stock as a realistic medium-run scenario before structural shifts in electricity supply occur. This flow-to-stock mapping allows us to study the electricity-market consequences of EV adoption without modeling a fleet accumulation model with transition dynamics.

We take the observed load, renewable generation, and merit order from calendar year 2023 as the electricity-market baseline. We use 2023 because earlier years were affected by COVID-19 and by the electricity-market disruptions following Russia's invasion of Ukraine. This combines the 2021 vehicle market equilibrium, which anchors the demand side of the model, with the more recent electricity-market conditions used to discipline dispatch. Below, we discuss scenarios where base demand or renewable generation supply increase.

We compare each counterfactual to a reference market in which no EVs are present. For each counterfactual, we begin from the 2021 vehicle market equilibrium, map annual EV sales into the implied EV stock using $N^{EV} = \Gamma Q^{EV}$, and compute the resulting EV load curves.[17] Using these load curves, we first solve the electricity market holding vehicle demand fixed, which yields the intermediate "no-feedback" outcome reported in the tables. We then iterate between the vehicle market and the electricity market, updating EV sales, the implied EV stock, charging demand, and electricity prices until the equilibrium conditions in (3.4) are satisfied.

For each scenario, we report changes in electricity generation and prices and implied EV stock and prices. We also compute total generation costs, given by the sum across all plants of marginal costs times generation, including emissions costs, plus ramping costs. 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.[18] Our contribution is to recover the marginal emissions

[16] In 2021 our sample contains 174,461 EV sales. A 10% EV share in a fleet of 48 million vehicles corresponds to 4.8 million EVs, implying $\Gamma = 0.10 \times 48{,}000{,}000/174{,}461 \approx 27.51$.

[17] Formally, EV load in interval s is $E_s^{EV} = \Gamma \sum_g \sum_i \sum_{j \in \chi_i} \pi_{ig} L_{gt} \sigma_{ijg} e^*_{ijgs}$, where π_{ig} are the type population weights described in Footnote 10.

[18] In this emissions accounting, we hold total miles traveled across inside vehicles and the outside good fixed, so changes in vehicle choice reallocate miles across options rather than changing aggregate travel. 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).

implied by the equilibrium generation response to EV demand, rather than infer emissions from average grid 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:

$$\Delta X^{elec} \equiv \underbrace{\sum_{s=1}^{S} \left[E_s^B \left(p_{s,\text{post}}^w + \mu^B\right) + E_s^{EV,h} p_{s,\text{post}}^h + E_s^{EV,a} p_{s,\text{post}}^a - E_s^B \left(p_{s,\text{pre}}^w + \mu^B\right)\right]}_{\text{Change in electricity expenditure}}$$

$$= \underbrace{\sum_{s=1}^{S} \left(E_s^{EV,h} p_{s,\text{post}}^h + E_s^{EV,a} p_{s,\text{post}}^a\right)}_{\text{Charging expenditure}} + \underbrace{\sum_{s=1}^{S} E_s^B \left(p_{s,\text{post}}^w - p_{s,\text{pre}}^w\right)}_{\text{Pecuniary externality}},$$

where we use $E_{s,\text{post}}^B = E_{s,\text{pre}}^B$, $E_{s,\text{pre}}^{EV} = 0$, and μ^B is the retail markup paid by baseline electricity consumers. The prices p_s^h and p_s^a already include the home- and public-charging markups. The pecuniary externality captures the extent to which EV adoption indirectly redistributes costs to non-EV users via higher base-load bills. The formulation highlights that the pecuniary externality of EV charging on other electricity users is most pronounced when EV-induced price increases coincide with high-demand periods.

6.2 Charging under Alternative Tariff Regimes

To evaluate alternative tariff regimes, we introduce a charging model that determines when EV drivers charge their vehicles over the day.

Under time-varying tariffs, households with home charging access reoptimize charging over the full price path subject to travel requirements and battery constraints. The resulting charging choices determine both the EV operating-cost terms entering demand and the intraday EV load profile entering dispatch. Appendix Section A.2 presents the dynamic charging problem and its mapping into aggregate EV load; here we focus on how these charging responses affect the equilibrium counterfactuals.

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 charging problem. 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 because different travel profiles purchase EVs when electricity rates 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.[19] 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-solving the charging problem in Appendix Section A.2 whenever the price sequence changes. This requires iterating 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 allocate charging quantity across the eight cheapest hours in which the consumer is at home, effectively spreading load across the relevant low-price periods. This pragmatic approximation mimics a real-world load management decision to spread charging across low-price periods.[20]

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

Table 4 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 4 shows that a 10% EV stock (4.8 million vehicles) requires 7.37 TWh of additional electricity and raises wholesale prices by €3.41/MWh, or 3.3%. EV adoption increases electricity-sector emissions by 5.65 million tonnes. In the

[19]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)

[20]Even with this allocation rule, the solution oscillates between two minor shadow peaks with nearly identical outcomes. We report results for one outcome and present both in Appendix Table A3.

Table 4: Electricity, Vehicle, Emissions, and Expenditures Outcomes

		Fixed price		**Time-varying price**	
	No EVs (1)	No feedback (2)	Full eq. (3)	No feedback (4)	Full eq. (5)
Electricity Market:					
Generation (TWh)	459.42	+7.37	+7.26	+7.36	+8.70
Weighted price (EUR/MWh)	102.62	+3.41	+3.37	+2.15	+3.16
Generation cost (bil EUR)	22.86	+0.92	+0.91	+0.69	+0.90
Vehicle Market:					
EV stock (1,000 units)		4,800	4,763	4,800	5,098
EV price		35,172	35,172	35,172	35,171
Emissions:					
Grid emissions (mio t)	123.63	+5.65	+5.56	+5.54	+6.48
Vehicle emissions (mio t)	71.55	-1.25	-1.34	-1.47	-1.75
EVs: gCO_2/km		105.11	103.47	101.46	101.04
Expenditures:					
EV charging (bil EUR)		+1.79	+1.79	+0.90	+1.09
Baseline (bil EUR)	47.15	+1.57	+1.55	+0.99	+1.45

Note:
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. "Baseline" denotes the pecuniary externality from EV-induced electricity price increases on baseline consumption. Vehicle emissions include EV grid emissions.

vehicle-emissions accounting, which includes the grid emissions from EV charging and the avoided tailpipe emissions from displaced combustion vehicles, total vehicle emissions decrease by 1.25 million tonnes, or 1.7%. This is a small decrease. EVs emit $105 gCO_2/km$ because they are often powered by gas and coal. As a comparison, the current EU fleet emissions target is $95 gCO_2/km$.[21] EVs' actual emissions would thus barely help firms reach the $95 gCO_2/km$ target if the EU assigned 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 €1.79 billion on charging. Strikingly, expenditures by non-EV users also rise by €1.57 billion due to higher electricity prices, indicating a sizable pecuniary externality. A 3.3% 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. The EV stock falls from 4.8 million to 4.76 million vehicles, a decline of less than 1%. A 3.3% 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 generation, emissions, and expenditure outcomes are virtually identical to the no-feedback case.[22] 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) keeps the EV stock fixed at 4.8 million but allows households to charge in response to time-varying prices rather than upon arrival at home. At this fixed stock, shifting charging across the day reduces the generation-cost increase from €0.91 billion to €0.69 billion and lowers the weighted-price increase from €3.41/MWh to €2.15/MWh. Charging expenditures fall from €1.79 billion to €0.90 billion, and the pecuniary externality falls from €1.57 billion to €0.99 billion. Time-varying pricing also slightly reduces grid emissions and lowers EV emissions intensity from 105 to 101 gCO_2/km.

Column (5) shows that much of this system-cost relief disappears once the full feedback loop is taken into account. Access to lower off-peak prices—often more than 20% below the flat tariff—makes EVs more attractive and raises the equilibrium EV stock to 5.10 million vehicles, about 335,000 more than under fixed prices in full equilibrium.[23] The larger EV stock raises generation by 8.70 TWh and pushes the weighted-price increase back up to

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

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

[23]As a comparison, around 520,000 EVs were sold in Germany in 2023.

€3.16/MWh. Total generation costs therefore return to €0.90 billion, essentially the same increase as under fixed prices, and the pecuniary externality rises to €1.45 billion, close to the €1.55 billion under fixed prices. Charging expenditures remain substantially lower, at €1.09 billion rather than €1.79 billion. At the same time, the larger EV stock increases total grid emissions, even though EV charging becomes slightly cleaner on average: emissions intensity falls from 103 to 101 gCO_2/km, and total vehicle emissions fall more. Overall, time-varying prices mainly lower private charging costs and encourage EV adoption, while doing less to reduce aggregate system costs once the equilibrium feedback is taken into account.

These effects quickly become more pronounced as the EV fleet grows. Appendix Table A4 repeats the exercise for EV stocks of 20% and 30%. At a 30% EV stock, weighted wholesale prices rise by €6.22/MWh under time-varying prices, more than 6% relative to the no-EV baseline, and by €6.09/MWh under fixed prices. The pecuniary externality on baseline electricity consumption also nearly doubles relative to the 10% EV-stock case.

Appendix Figure A4 illustrates how a 10% EV stock changes intraday electricity load curves under different pricing schemes. The figure shows that time-varying pricing shifts load away from the evening peak into night and midday hours.

Table 5 reports changes in generation profits by energy source. The increase in electricity-sector profits reflects two forces: margins on the additional electricity sold to EVs and higher margins on the pre-existing base load when EV demand raises wholesale prices. Under fixed prices, total profits rise by 1.64% in full equilibrium. Under time-varying prices, the corresponding increase is slightly larger, at 1.79%.

The distribution of profit gains differs sharply across technologies. Under fixed prices, EV load is concentrated in hours when thermal plants often set the marginal price. In full equilibrium, profits rise by 18.82% for lignite, 25.82% for coal, and 34.84% for gas, while renewable profits rise by only 0.34%. These large percentage gains for fossil technologies reflect the combination of higher output and higher inframarginal rents in hours when EV charging increases wholesale prices.

Time-varying prices dampen these fossil-profit gains by shifting EV charging toward lower-price hours. At a fixed EV stock, the profit increases for lignite, coal, and gas fall to 7.27%, 7.00%, and 8.81%, respectively. Once EV adoption responds endogenously, the larger EV stock raises fossil profits again, but the gains remain below those under fixed prices: 14.61% for lignite, 19.23% for coal, and 26.79% for gas. Renewable profits, by contrast, rise more under time-varying prices in full equilibrium, increasing by 1.07% rather than 0.34% under fixed prices.

Hence, time-varying pricing reduces the relative advantage of fossil generators and shifts short-run rents toward renewable producers. Because these rents enter expected returns to

Table 5: 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)	51.32	+1.69%	+1.64%	+0.48%	+1.79%
Profits by source:					
Renewables (bil EUR)	25.37	+0.37%	+0.34%	+0.36%	+1.07%
Lignite (bil EUR)	0.98	+19.21%	+18.82%	+7.27%	+14.61%
Coal (bil EUR)	0.47	+26.38%	+25.82%	+7.00%	+19.23%
Gas (bil EUR)	0.28	+35.61%	+34.84%	+8.81%	+26.79%

Note:
Column (1) reports baseline profits without EVs in billion EUR. Columns (2)–(5) report percentage changes relative to the no-EV baseline. 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.

capacity, this pattern suggests that time-varying pricing can strengthen renewable investment incentives. At the same time, our exercise is a static equilibrium with fixed generation capacity. Modeling endogenous entry is beyond the scope of the paper, especially because entry into the electricity market is highly regulated and depends on network capacity as well as investors' long-run expectations of the EV stock.

6.4 EV adoption and electricity market transition

Table 6 examines scenarios reflecting ongoing transitions in the electricity market. We consider three scenarios. 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 hourly electricity demand by 10%, representing broader electrification and load growth from sources such as heating, industry, or data centers.

When we increase the ETS price, the effect on EV adoption depends strongly on the tariff regime. Under fixed electricity rates, EV adoption changes little: the EV stock falls from 4.76 million to 4.74 million vehicles. The main effect is on prices and costs. The weighted wholesale-price increase rises from €3.37/MWh to €5.69/MWh, generation costs rise from €0.89 billion to €1.43 billion, and the pecuniary externality rises from €1.55 billion to €2.61 billion. EV emissions intensity is essentially unchanged, increasing slightly from

Table 6: EV Adoption and Electricity Market Transition Scenarios

	No EVs (1)	Baseline (2)	ETS (3)	Renewables (4)	Demand (5)
			Fixed price		
Electricity Market:					
Generation (TWh)	459.42	+7.26	+5.34	+7.39	+7.14
Weighted price (EUR/mWh)	102.62	+3.37	+5.05	+2.87	+3.18
Generation cost (bil EUR)	22.86	+0.91	+1.06	+0.91	+0.93
Vehicle Market:					
EV stock (1,000 units)		4,763	4,096	4,808	4,727
EV price		35,172	35,175	35,172	35,172
Emissions:					
Grid emissions (mio t)	123.63	+5.56	+4.10	+5.48	+5.49
Vehicle emissions (mio t)	71.55	-1.34	-0.99	-1.55	-1.31
EVs: gCO2/km		103.47	103.28	100.02	103.64
Expenditures:					
EV charging (bil EUR)		+1.79	+1.70	+1.79	+1.79
Baseline (bil EUR)	47.15	+1.55	+2.32	+1.32	+1.53
			Time-varying price		
Electricity Market:					
Generation (TWh)	459.42	+8.70	+6.69	+9.03	+9.42
Weighted price (EUR/mWh)	102.62	+3.16	+4.84	+2.24	+2.38
Generation cost (bil EUR)	22.86	+0.90	+1.05	+0.83	+0.92
Vehicle Market:					
EV stock (1,000 units)		5,098	4,466	5,220	5,331
EV price		35,171	35,170	35,171	35,173
Emissions:					
Grid emissions (mio t)	123.63	+6.48	+4.25	+6.20	+7.30
Vehicle emissions (mio t)	71.55	-1.75	-2.13	-2.41	-1.76
EVs: gCO2/km		101.04	85.52	92.35	103.39
Expenditures:					
EV charging (bil EUR)		+1.09	+1.03	+1.09	+1.19
Baseline (bil EUR)	47.15	+1.45	+2.22	+1.03	+1.15

Note:
Columns (1) and (2) replicate the baseline equilibrium without and with EVs (as in Table 4). 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%, and (5) a uniform 10% increase in demand in all periods. "Weighted price" denotes the average load-weighted wholesale price. "Baseline" denotes the pecuniary externality—i.e., the change in electricity costs for baseline consumers resulting from EV-induced price increases. Vehicle emissions include EV grid emissions.

$103 gCO_2/km$ to $104 gCO_2/km$. With fixed tariffs, higher carbon prices therefore mostly raise the electricity-market costs associated with EV load and the spillover on baseline electricity consumers, without materially changing EV adoption.[24]

Under time-varying prices, the ETS increase has a different effect because it changes relative prices across hours. EV users can shift charging away from carbon-intensive hours whose marginal costs rise most. EV adoption increases from 5.10 million to 5.29 million vehicles, while EV emissions intensity falls from $101 gCO_2/km$ to $86 gCO_2/km$. Grid emissions from EV charging also fall, from 6.48 million tonnes to 6.02 million tonnes, despite higher EV adoption. This comes at higher system cost: generation costs rise from €0.89 billion to €1.48 billion and the pecuniary externality rises from €1.45 billion to €2.57 billion.

In the renewable-expansion scenario, increasing renewable capacity by 10% lowers the electricity-market cost of EV adoption and improves its emissions performance. Under fixed prices, the weighted-price increase falls from €3.37/MWh to €2.83/MWh, and the pecuniary externality falls from €1.55 billion to €1.30 billion. The EV stock is almost unchanged, but EV emissions intensity falls from $103 gCO_2/km$ to $100 gCO_2/km$. Time-varying prices amplify these benefits. With additional renewable capacity, EV adoption rises from 5.10 million to 5.18 million vehicles, while the weighted-price increase falls from €3.16/MWh to €2.20/MWh, generation costs fall from €0.89 billion to €0.82 billion, and the pecuniary externality falls from €1.45 billion to €1.01 billion. EV emissions intensity declines to $92 gCO_2/km$.

In the demand-growth scenario, the effects again depend on the tariff regime. Under fixed prices, the equilibrium EV stock falls slightly, from 4.76 million to 4.73 million vehicles. Relative to the baseline fixed-price case, the incremental effect of EV adoption on electricity prices is slightly smaller: the weighted-price increase falls from €3.37/MWh to €3.18/MWh, and the pecuniary externality falls from €1.55 billion to €1.53 billion. Generation costs rise slightly, from €0.91 billion to €0.93 billion. Emissions outcomes are also very similar. Grid emissions attributed to EV charging fall from 5.56 million tonnes to 5.49 million tonnes, while EV emissions intensity is essentially unchanged, rising from $103 gCO_2/km$ to $104 gCO_2/km$. Thus, with fixed tariffs, higher background demand has only a modest effect on the incremental costs and emissions associated with EV adoption.

Under time-varying prices, higher background demand raises the equilibrium EV stock from 5.10 million to 5.33 million vehicles. The weighted-price increase falls from €3.16/MWh to €2.38/MWh, and the pecuniary externality declines from €1.45 billion to €1.15 billion. However, the larger EV stock raises EV-related generation from 8.70 TWh to 9.42 TWh,

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

generation costs from €0.90 billion to €0.92 billion, and charging expenditures from €1.09 billion to €1.19 billion. Grid emissions attributed to EV charging increase from 6.48 million tonnes to 7.30 million tonnes, and EV emissions intensity rises from 101gCO_2/km to 103gCO_2/km.

In sum, time-varying electricity prices make EV adoption more responsive to changes in the composition and costs of electricity supply. They allow EV users to benefit from renewable expansion and to avoid the most carbon-intensive hours when carbon prices rise. Under stronger background demand growth, they continue to dampen the pecuniary externality from EV load, but they also stimulate additional EV adoption, which raises EV electricity use, charging expenditures, and grid emissions.

7 Conclusion

We develop and estimate a joint equilibrium model linking vehicle adoption, individual charging decisions, and electricity market outcomes. The model connects the vehicle and electricity markets through the charging decision: vehicle choices determine the level and timing of electricity demand, while electricity prices enter EV operating costs and feed back into vehicle adoption.

Our first result is that this feedback is weak under fixed retail electricity prices. A 10% EV stock raises weighted wholesale electricity prices by about 3.3% and generates sizable spillovers on non-EV electricity users, but the resulting increase in EV operating costs reduces EV adoption by less than 1%. This finding is important because the market does not self-correct much through the adoption margin: rapid EV diffusion without a commensurate expansion of electricity supply can raise electricity costs for other users without materially slowing the growth of the EV fleet.

Time-varying pricing changes the feedback. When EV adoption is held fixed, exposing home charging to hourly wholesale-price variation shifts charging toward lower-cost hours, reducing generation costs, charging expenditures, and the spillover on baseline electricity users. In the full equilibrium, however, these gains are substantially attenuated. Lower charging costs make EVs more attractive, increasing EV adoption and aggregate charging demand. Time-varying pricing therefore lowers private charging costs and modestly reduces EV emissions intensity, but it does not fully eliminate the aggregate cost pressure created by transport electrification.

Time-varying pricing becomes especially valuable as the electricity sector changes. When carbon prices rise, electricity demand from other sectors grows, or renewable supply expands, the relative cost of charging varies more across hours. Fixed tariffs prevent EV users from responding to this variation. Time-varying prices allow them to shift charging toward lower-cost hours, helping sustain EV adoption while improving the alignment between charging demand and the changing electricity system.

Overall, our findings suggest that EVs and electricity markets are strongly complementary: adoption affects electricity prices and producer rents, while electricity pricing shapes both the private cost and system cost of electrifying transport. Policies for vehicle electrification and electricity pricing should therefore be designed jointly.

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.

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.*

Barwick, Panle Jia, Hyuk-Soo Kwon, Shanjun Li, and Nahim B Zahur. 2025. "Drive down the cost: Learning by doing and government policies in the global EV battery industry." National Bureau of Economic Research.

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.

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.

Elliott, Jonathan T. 2026. "Investment, Emissions, and Reliability in Electricity Markets." *Working Paper.*

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. 2026. "Fueling electrification: The impact of gas prices on hybrid car usage." *Journal of the Association of Environmental and Resource Economists*, 13(3): 681–711.

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.

Head, Keith, Thierry Mayer, Marc Melitz, and Chenying Yang. 2026. "Industrial Policies for Multi-Stage Production: The Battle for Battery-Powered Vehicles." National Bureau of Economic Research NBER Working Papers 34884.

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.

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.

Jia Barwick, Panle, Shanjun Li, and Tianli Xia. 2026. "Range Anxiety." National Bureau of Economic Research NBER Working Papers 34871.

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. 2026. "Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles." *American Economic Journal: Economic Policy*, 18(2): 107–140.

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.*

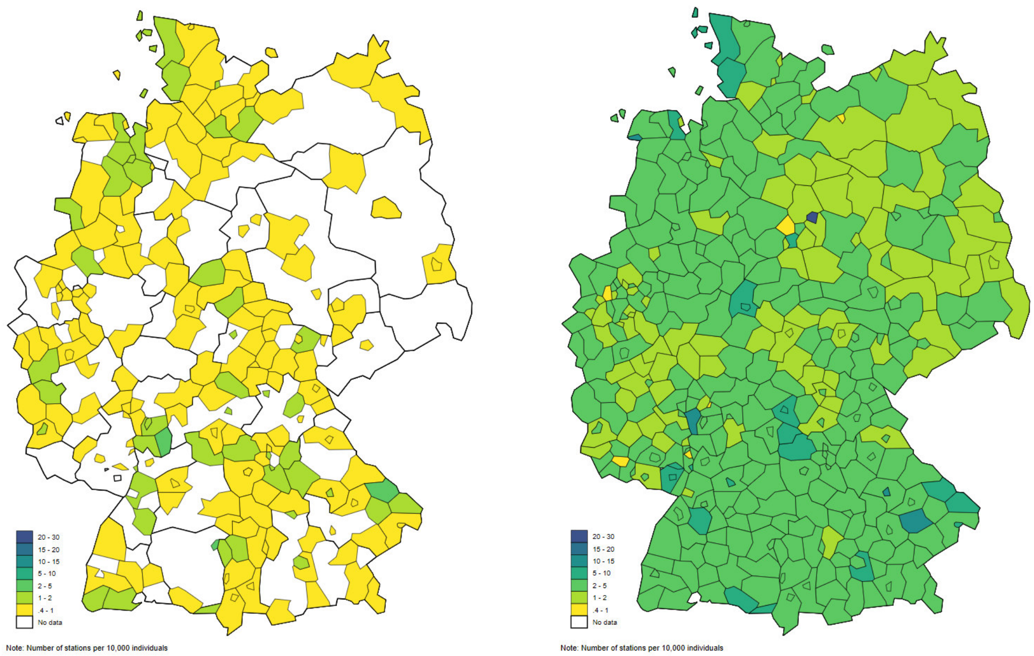
Springel, Katalin. 2021. "Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives." *American Economic Journal: Economic Policy*, 13(4): 393–432.

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

A Appendix

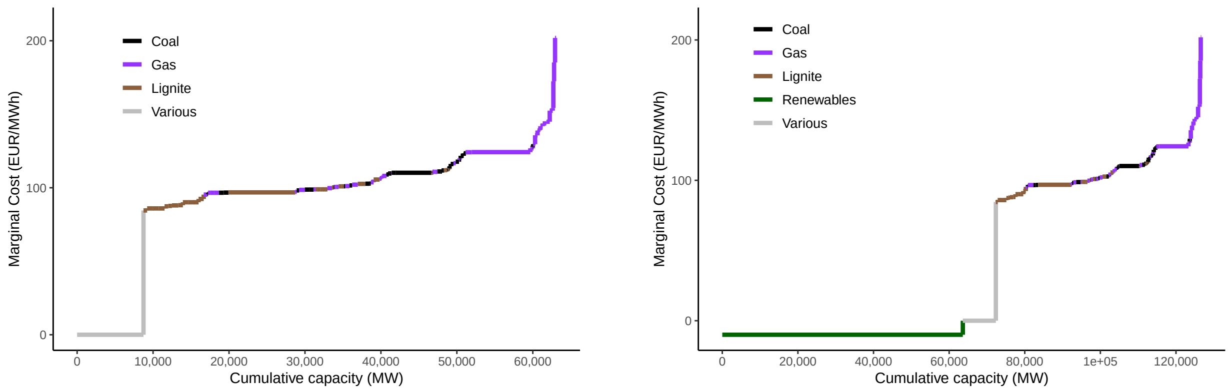
A.1 Additional Figures and Tables

Figure A1: Public chargers per 10,000 inhabitants by county



2017 2021

Figure A2: Merit order curves with no and maximal renewable generation



No renewable generation | Maximum observed renewable generation

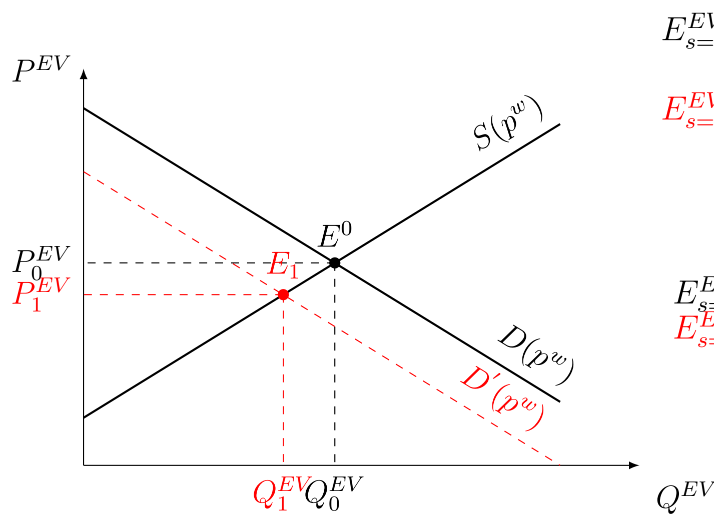
Note: The figure plots the merit-order curve without renewable generation (left) and with maximum renewable generation (right). Generators are ordered by marginal cost c_u, and the cumulative capacity is plotted on the horizontal axis.

Table A1: Generation Unit Summary Statistics

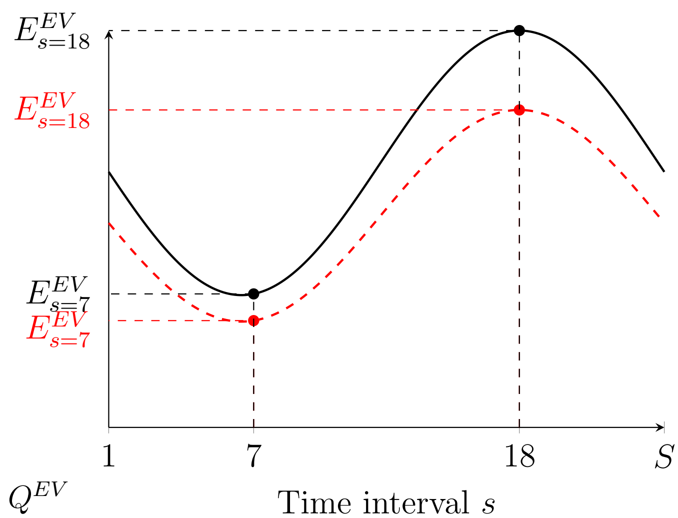
	Avg. MC (EUR/MWh)	Avg. Unavail. (%)	Avg. EI (tCO_2/MWh)	Cap. (GW)	Production (TWh)	Prod. Share (%)
Renewables	0.00	—	0.00	63.62	236.57	47.4
Named thermal						
Named gas	124.24	31.6	0.20	18.13	31.25	6.3
Named lignite	96.84	29.6	0.40	18.02	76.68	15.4
Named coal	110.19	50.5	0.34	17.84	34.80	7.0
Generic thermal						
Generic gas	124.24	—	0.20	7.71	22.99	4.6
Generic lignite	96.84	—	0.40	8.80	1.28	0.3
Generic coal	110.19	—	0.34	4.67	9.72	1.9
Other						
Imports	92.47	—	0.16	33.79	63.75	12.8
Various	0.00	—	0.00	8.74	21.89	4.4

Notes: Avg. MC for named thermal = avg. fuel price + estimated VOM ($\hat{\nu}_\kappa$). Generic plants use observed production; their MC equals the mean fuel price of named counterparts with no VOM adjustment. Unavailability is not reported for generics, imports, renewables, or various as these are fixed in the dispatch. Emission intensity for named thermal uses plant-level factors from the power plant registry; import intensity is production-weighted across countries using Ember (2023) grid intensities. Production share is share of total observed generation across all groups.

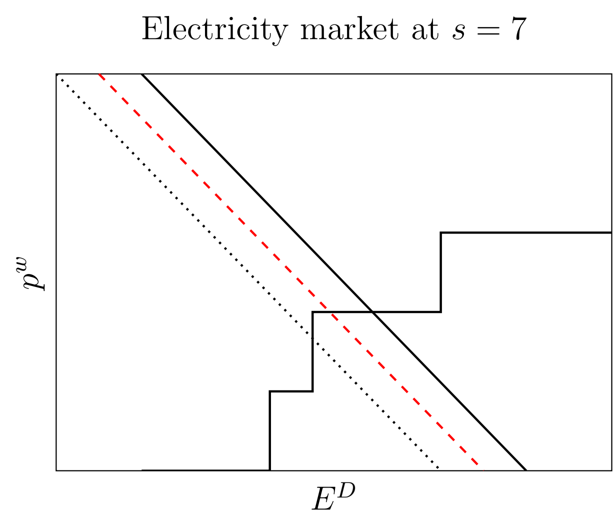
Figure A3: Schematic overview of complementarity between EV and electricity markets

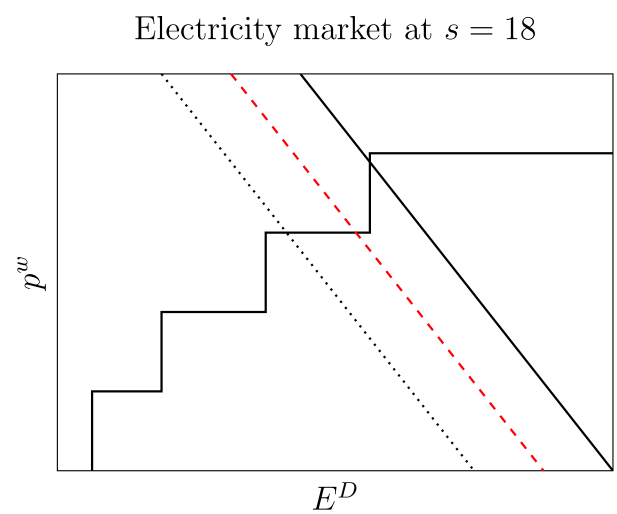


(a) Vehicle demand–supply



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





$E_{s=7}^{B}$ $E_{s=7}^{B} + E_{s=7}^{EV}$ $E_{s=7}^{B} + E_{s=7}^{EV}$ $E_{s=18}^{B}$ $E_{s=18}^{B} + E_{s=18}^{EV}$ $E_{s=18}^{B} + E_{s=18}^{EV}$

(d) Electricity market, $s = 18$

(c) Electricity market, $s = 7$

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 an 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. Panels (a)–(d) are connected because $p^a = f(p^w), p^h = f(p^w)$ and because E_s^{EV} is a function of the vehicle quantity, which depends on electricity prices.

Figure A4: Comparison of actual and counterfactual load curves

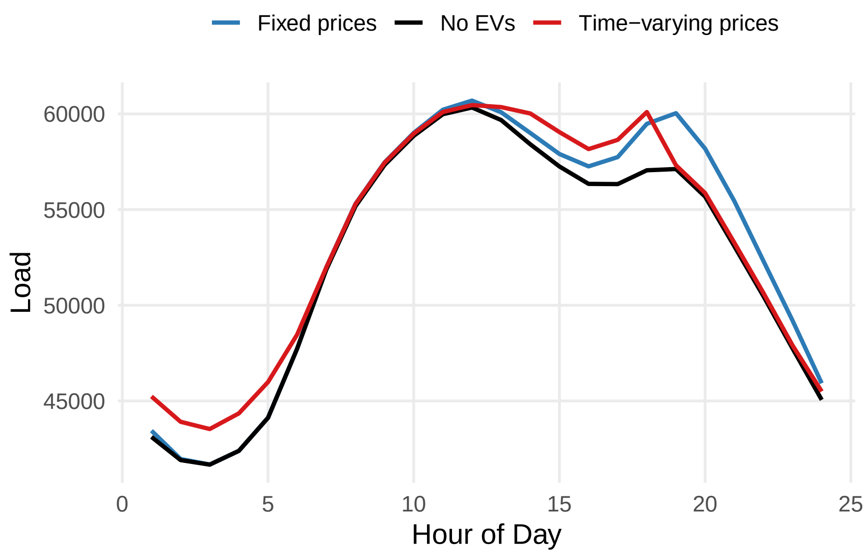


Table A2: Input Fuel and Carbon Prices, 2023

	Mean	Min	Max	Unit
Natural gas (TTF)	41.28	23.11	74.30	EUR/MWh
Coal (API2 Rotterdam)	127.14	93.25	184.65	EUR/t
Lignite	3.10	—	—	EUR/MWh$_{th}$
ETS (EU EUA)	84.60	66.73	97.47	EUR/tCO$_2$

Notes: Daily prices for 2023 trading days. Gas: TTF front-month futures (EUR/MWh). Coal: API2 Rotterdam steam coal (EUR/t). Lignite: fixed extraction cost assumption (EUR/MWh$_{th}$); no liquid market. ETS: EU Emission Trading System allowance (EUA) spot price (EUR/tCO$_2$).

Table A3: Comparison of Alternate Shadow Peaks

	No EVs	Eq. 1	Eq. 2
Electricity Market:			
Generation (TWh)	459.42	+8.70	+8.70
Weighted price (EUR/MWh)	102.62	+3.16	+3.12
Generation cost (bil EUR)	22.86	+0.90	+0.91
Vehicle Market:			
EV stock (1,000 units)		5,098	5,100
EV price		35,171	35,171
Emissions:			
Grid emissions (mio t)	123.63	+6.48	+6.48
Vehicle emissions incl. EV grid (mio t)	71.55	-1.75	-1.75
EVs: gCO_2/km		101.04	101.03
Expenditures:			
EV charging (bil EUR)		+1.09	+1.10
Baseline (bil EUR)	47.15	+1.45	+1.43

Note: This Table replicates Table 4 for time-varying prices but shows in Eq. 1 and Eq. 2 the outcomes at the two shadow peaks at which the solution oscillates.

Table A4: Outcomes at different EV stock sizes

		10% EV Stock		**20% EV Stock**		**30% EV Stock**	
Variable	No EVs (1)	Fix (2)	Varying (3)	Fix (4)	Varying (5)	Fix (6)	Varying (7)
Electricity Market:							
Generation (TWh)	459.42	+7.26	+8.70	+14.42	+17.93	+21.49	+27.69
Weighted price (EUR/MWh)	102.62	+3.37	+3.16	+4.67	+3.97	+6.09	+6.22
Generation cost (bil EUR)	22.86	+0.91	+0.90	+1.33	+1.38	+1.91	+2.11
Vehicle Market:							
EV stock (1,000 units)		4,763	5,098	9,498	10,311	14,199	15,757
EV price		35,172	35,171	35,172	35,171	35,172	35,171
Emissions:							
Grid emissions (mio t)	123.63	+5.56	+6.48	+7.65	+10.19	+9.51	+11.55
Vehicle emissions (mio t)	71.55	-1.34	-1.75	-6.07	-6.69	-28.14	-31.09
EVs: gCO_2/km		103.47	101.04	71.54	77.42	59.72	57.12
Expenditures:							
EV charging (bil EUR)		+1.79	+1.09	+3.58	+2.25	+5.36	+3.60
Baseline (bil EUR)	47.15	+1.55	+1.45	+2.15	+1.82	+2.80	+2.86

Note:
"Weighted price" is the average load-weighted wholesale price. "Baseline" denotes the pecuniary externality from EV-induced electricity price increases on baseline consumption. Vehicle emissions include EV grid emissions.

A.2 Charging under time-varying tariffs

To compute EV operating costs under time-varying tariffs, we solve a finite-horizon cost-minimization problem for each individual travel profile w_i, vehicle j, and market gt. The travel profile is $w_{is} = (h_{is}, r_{is}, m_{is})$, where h_{is} indicates whether the individual is at home, r_{is} indicates driving, and m_{is} records kilometers driven in interval s. Let o_s indicate whether public charging is available in interval s; in the empirical implementation, $o_s = 0$ between 11 p.m. and 6 a.m. and $o_s = 1$ otherwise. Vehicle j is characterized by battery capacity R_j and electricity consumption e_j in kWh/km. Let B_s denote the battery level at the beginning of interval s, and let C denote the amount that can be charged within one interval. The battery state must satisfy

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

We initialize and close the repeated travel sequence with a full battery, $B_1 = B_{S+1} = R_j$, so the profile can be repeated without terminal depletion.

For exposition, we suppress all indices except s. In each interval, the individual decides whether to charge, with decision $c_s \in \{0, 1\}$. Battery dynamics follow

$$B_{s+1} = \mathbb{1}\{r_s = 0\}\left(B_s + c_s \min\{C, R - B_s\}\right) + \mathbb{1}\{r_s = 1\}\left(B_s - m_s e\right) \tag{9}$$

for all $s \in \{1, \ldots, S\}$. When the individual is driving, the battery falls by $m_s e$. Otherwise, the vehicle either charges or remains idle. Travel profiles that would violate the battery constraints for a given EV are infeasible, and the corresponding EV is removed from the individual's choice set χ_i.

We distinguish households without and with home charging access. For individuals without home charging ($l = 0$), all charging occurs at public stations and the dynamic problem is

$$\begin{aligned} V_s^{l=0}(B_s) = \min_{c_s} \left[\mathbb{1}\{r_s = 0\} c_s p_s^a \min\{C, R - B_s\} + V_{s+1}^{l=0}(B_{s+1})\right] \qquad (10) \\ \text{s.t. } 0 \leq B_s \leq R, \quad c_s \leq (1 - r_s) o_s \quad \forall s \in \{1, \ldots, S\}. \end{aligned}$$

For individuals with home charging access ($l = 1$), charging costs depend on whether the vehicle is at home:

$$V_s^{l=1}(B_s) = \min_{c_s} \Big[\mathbb{1}\{r_s = 0\} c_s \left(\mathbb{1}\{h_s = 1\} p_s^h + \mathbb{1}\{h_s = 0\} p_s^a \right) \min\{C, R - B_s\} + V_{s+1}^{l=1}(B_{s+1}) \Big] \tag{11}$$

$$\text{s.t. } 0 \le B_s \le R, \quad c_s \le (1 - r_s)\left[h_s + (1 - h_s) o_s\right] \quad \forall s \in \{1, \dots, S\}.$$

These Bellman equations formalize the idea that households are forward-looking: they compare the current cost of charging to the value of preserving battery charge for later intervals with different travel needs and electricity prices.

The solution yields optimal charging decisions $(c^*_{ijgts})_{s=1}^S$ and implied charging quantities at home and at public stations, $(e^{h*}_{ijgts}, e^{a*}_{ijgts})_{s=1}^S$. These charging quantities determine the expenditure terms entering vehicle demand,

$$A_{ijgt}^{l_i} = \sum_{s=1}^{S} e^{a*}_{ijgts} p^a_{tgs}, \qquad H_{ijgt}^{l_i=1} = \sum_{s=1}^{S} e^{h*}_{ijgts} p^h_{tgs},$$

and they aggregate into the EV load profile entering electricity demand:

$$E_{ts}^{EV} = \sum_g \sum_i \sum_{j \in \chi_i} \pi_{ig} L_{gt} \sigma_{ijgt} \left(e^{h*}_{ijgts} + e^{a*}_{ijgts} \right). \tag{12}$$

In the counterfactuals in Section 6, we multiply this flow-based object by the fixed scaling factor that maps 2021 EV sales into the counterfactual EV stock.

In the fixed-price counterfactual, the residential tariff is constant within the day, so intraday timing does not affect the monetary cost of a given home-charging profile. We therefore retain the baseline arrival-home charging pattern and update only the resulting expenditures as equilibrium prices change. In the time-varying tariff counterfactual, by contrast, we set $p_s^h = p_s^w + \mu^h$ and recompute the solution to (11) whenever the wholesale price sequence changes. This is the additional step that links hourly price variation to both EV operating costs and the equilibrium load profile reported in Section 6.

A.3 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 A5 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.

Table A5: 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

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 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.