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

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Abstract

The transition to electric vehicles (EVs) shifts the complementary market for passenger transport from oil to electricity. We develop and estimate a joint equilibrium model of the German electricity and automobile markets, emphasizing the timing of EV charging, as electricity generation costs and pollution vary intraday. Our results show that under Germany's current electricity pricing scheme, EVs create a significant pecuniary externality: electricity expenses rise by €0.66 for every €1 spent charging. Exposing charging to wholesale price variation eliminates the pecuniary externality, makes EVs greener, and increases adoption—a triple dividend.

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

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1 Introduction

The automobile sector is undergoing a rapid and drastic transformation. While electric vehicles (EVs) were a rare sight just a decade ago, they now account for 18% of global sales, supported by various subsidy schemes International Energy Agency (2024). This transition shifts the complementary market for transportation from oil-based products to electricity. Unlike global oil markets, electricity markets are characterized by local systems and substantial intraday price fluctuations. Rapid electrification poses the risk of driving up electricity prices, which could reduce consumer demand for EVs by increasing their operating costs.

This paper constructs a structural equilibrium framework to analyze the interaction between electricity and automobile markets. We estimate the model by focusing on the recent electrification of the German automobile market, where battery electric vehicles (BEVs) have grown to represent over 18% of new vehicle sales in recent years. The German electricity market has substantial intraday fluctuations in generation costs. The average wholesale price is around €100/MWh, but hourly prices can range from as low as €75/MWh to as high as €125/MWh. In other words, electricity generation costs fluctuate by an average of 66% in a single day.[1] In contrast, retail and charging station prices are time-invariant intraday. The marginal energy supply in the German market shifts between wind, solar, gas, and coal depending on the time of day. As quantified by Holland et al. (2016), EVs can be more polluting than combustion vehicles when charged during hours when coal is the marginal energy source.

We use the model to answer the following research questions. How does EV adoption affect electricity prices? Will rising electricity prices act as a backstop on EV adoption? How critical are time-varying electricity rates for EV adoption and electricity prices? How does the interaction between the automobile market and the electricity market depend on electricity generation expansion? Our model answers these questions in the German context and provides a blueprint for studying these questions in other geographical markets.

The joint equilibrium model makes three critical contributions. First, the model explicitly accounts for intraday vehicle usage and charging patterns. Intraday charging patterns matter to correctly predict the electricity generation costs and environmental implications of EV charging. Second, we show that additional electricity demand from vehicles during peak hours risks increasing electricity prices economy-wide, introducing a potentially important pecuniary externality from electrification. Third, consumer EV adoption decisions depend on electricity prices as they affect EV operating costs. As rising EV demand pushes up electricity

[1] By contrast, gasoline prices typically fluctuate by 3-4% daily and varied by around 10% for 2023.

prices, the resulting operating cost increase could dampen further EV adoption. We model the complementary equilibrium by specifying a charging cost minimization problem, a vehicle demand model, and an electricity market model.

The charging cost minimization problem maps exogenous individual driving patterns to the amount and timing of battery charging needed for operating an EV. We frame this as a finite-horizon dynamic discrete choice problem, where individuals plan their charging based on their anticipated driving needs over a limited time horizon. The model is related to the charging model for commercial battery operators by Butters et al. (2021), but it differs due to our focus on private EV owners.

The charging model incorporates EV owners' exogenous driving demand, home status, and access to home charging. We do not allow EV owners to resell their charged energy; driving is the only way to deplete the battery. Solving this model allows us to determine the lowest cost of electricity from home and public charging for each individual and EV combination in a given market.

The charging model enables us to obtain intraday electricity load profiles from EVs and compute expected electricity costs as a function of vehicle choices. We rely on responses of over sixty thousand respondents to the mobility survey "Mobilität in Deutschland 2017" to construct individual driving profiles. For each of these profiles, every EV model available on the German market, and for each region, we calculate more than 11 million optimal charging patterns.

The demand model estimates which individuals with associated charging patterns purchase an EV. We expand Berry et al. (1995) and estimate a demand model using car registration data that carefully models the choice between EVs and combustion engines. Heterogeneous consumers, defined by their travel profiles, choose among differentiated vehicles. We extend the standard model by integrating the solutions from the optimal charging model, which allows us to calculate monetary electricity costs for each vehicle for all travel profiles. This is similar to the modeling in Jia Barwick et al. (2022b), where they incorporate optimal transport mode choice into a housing location choice model.

Our demand model also accounts for different levels of disutility for refueling, home charging, and public charging. Additionally, we allow the disutility of charging to change with the charging station density, capturing how improvements in the availability of charging infrastructure affect preferences for EVs.

We estimate the demand model using German vehicle registration and attribute data between 2012 and 2021. Our estimation accounts for endogenous vehicle prices and the indirect network effect between charging stations and vehicle demand, following Springel (2021). We extend the standard approach, which matches observed market shares, by incorporating additional moments that match observed electricity demand at charging stations. For each region and hour, we observe electricity consumption at charging stations. The data show consumers begin charging vehicles around 7 am at public chargers, with a steady demand for electricity during the day. Electricity demand at stations increased starkly after 2016, coinciding with the rise in electric vehicle sales and the resulting growth of the EV car stock. Matching the charging station data is crucial to identify which consumers charge at home and the disutility of home and away charging.

Finally, we model the electricity market. Our vehicle demand model provides individual choice probabilities linked to optimal charging profiles. By integrating over these estimated choice probabilities, we derive an intraday electricity load curve for electric vehicle charging. We set up an empirical model of the German electricity supply using a merit order framework. We assume the electricity demand not stemming from vehicles to be inelastic and fixed. Although we do not account for trading, congestion, and ramp-up costs, our model performs well in explaining electricity price variation. The correlation between simulated and observed hourly prices in 2023 is 0.72. However, the model does not fully capture price extremes, particularly peaks and troughs related to ramp-up costs and renewable energy subsidies.

We use the estimated joint equilibrium model to study EV adoption consequences under two scenarios. In the first scenario, we consider consumers are shielded from the intraday energy wholesale price fluctuations due to time-invariant price contracts. This is the current retail pricing schedule in Germany (and in many other countries). EV chargers have no incentive to charge during off-peak hours, despite the cost and equilibrium implications of charging at peak hours, leading to inefficiencies Joskow and Wolfram (2012). In the second scenario, we quantify the importance of exposing EV chargers to intraday electricity price variation.[2] In both scenarios, we evaluate an equilibrium with no EVs, with one in which EVs take up 10% of the vehicle stock, which would equal 4.8 million EVs before we recompute the equilibrium.[3] At the end of 2023, the EV stock in Germany reached 1.4 million, and the German government aims to have 15 million EVs on the road by 2030.

Our analysis reveals three main insights when electricity prices are constant across the day, as is currently the case in Germany. First, we find that a 10% EV stock increases wholesale prices by €1.60 and imposes a substantial pecuniary externality on electricity users. Every Euro spent on charging imposes a cost of around 66 cents on electricity users.[4]

[2] Bailey et al. (2024) find in an experiment that time-of-use pricing creates shadow peaks due to simultaneous charging. We find the same issue in our simulations. In practice, network operators will likely have to combine time-of-use pricing with quantity smoothing over low-priced periods.

[3] Our demand model estimates a flow of vehicle sales. We multiply this flow with a fixed factor to obtain 4.8 million EV sales from the 2021 flow. We then consider equilibrium changes in the flow but keep the fixed multiplication factor.

[4] In our exercise, we keep oil-based fuel prices (diesel and gasoline) constant. When electric vehicles

Second, the increase in electricity prices has negligible effects on EV adoption. Electricity prices increase by about 1%, which is not enough to make EV buyers switch back to combustion engines. Electricity price increases will not create a backstop on EV adoption. Third, we find that EVs emit around 91 gCO2/km through polluting energy generation. The current EU fleet emission standard is 95 gCO2/km. EVs barely comply with the standard when taking into account actual emissions. We find that even a 10% increase in renewable generation reduces per-km CO2 emissions of EVs only by around 3g and barely changes the pecuniary externality. When we expand pre-existing electricity demand by 10%, the pecuniary externality increases to 87 cents, and EVs become more polluting.

In the second scenario, we change the electricity rates in Germany to vary throughout the day. Several governments are experimenting with time-varying rates to try and incentivize EV owners not to charge during peak hours.[5] The advantage of our model is that we can solve optimal charging decisions for time-varying electricity rates and study the equilibrium effects on EV demand and electricity markets. We focus on a hypothetical scenario where every EV would charge optimally given a known sequence of prices. Such a scenario would mimic one where each household has a device that makes cost-minimizing charging decisions to satisfy their travel patterns.

We find that exposing EV chargers to time-varying prices generates a triple dividend: the pecuniary externality of EV charging almost disappears and shrinks to less than 10 cents per €1 charged, EVs become much greener because the emissions from charging shrink by 30%, and EV adoption expands. The expansion of EV adoption comes from the substantial drop in operating costs. If EV chargers can access low-priced electricity charging, they can charge at rates that are substantially lower than the fixed rates.

Overall, our results showcase that electrifying German transport without time-varying prices will be costly because of the higher peak prices and polluting because peak demand is often supplied by carbon-intensive coal generation. While we find that electricity rate increases from a 10% EV stock do not stop EV adoption, adoption would increase more if EV chargers could benefit from times when wholesale electricity prices are low.

We contribute to a young and fast-growing literature studying the EV transition. One strand of this literature has focused on different aspects of EV adoption while treating electricity markets as exogenous. The EV adoption literature has focused on charging stations

replace substantial shares of combustion engines globally, one might expect oil prices to decrease and fuel stations to exit. Our model does not consider this and keeps fuel prices and fuel station availability constant.

[5]For example, Bailey et al. (2025) work with a Canadian retailer to expose consumers to time-varying prices. TXU Energy, a retailer in Texas, offers free night-time charging for Ford EV owners, see `https://www.txu.com/en/electricity-plans/free-ev-miles-ford`. PG&E the utility serving most of central and northern California including the San Francisco Bay Area, offers time-of-use rates for EVs, see `https://www.pge.com/en/account/rate-plans/find-your-best-rate-plan/electric-vehicles.html`.

(Li et al. (2017), Li (2019), Springel (2021), Li (2019), and Fournel (2021)), purchase subsidies (Xing et al. (2021) and Muehlegger and Rapson (2022)), supply-side responses to subsidies (Armitage and Pinter (2021), Jia Barwick et al. (2022a) and Remmy (2023)), and usage costs (Sinyashin (2021), Bushnell et al. (2022), and Dorsey et al. (2022)). Another strand of the EV literature studies the effects of EVs on electricity markets, treating EV adoption as exogenous (Holland et al. (2016), Holland et al. (2022), Burlig et al. (2021), Holland et al. (2016), Gillingham et al. (2024) and Bailey et al. (2024)). Our prime contribution is treating both the vehicle and electricity as endogenous in a joint-equilibrium framework rather than considering either side of the market as exogenous.

We make three further contributions to this literature. First, we provide a model that connects EV adoption to the electricity market at a very granular level. In particular, our model gives rise to endogenous charging patterns and, in consequence, endogenously changing electricity load curves. This allows us to study a rich set of counterfactuals to evaluate how EV policies can shape load curves and the environmental benefits of EVs.

Second, we provide a model of optimal individual battery charging and EV use. Doing so allows us to obtain realistic substitution patterns between conventional and electric cars that depend on individual usage patterns. Our battery charging model also allows us to micro-found the role of EV range and charging station availability in EV adoption and to predict home-charging patterns, which are very difficult to observe, even if one has access to residential electricity consumption data.

Third, we provide an EV choice model that incorporates a disutility for home and away charging, allowing for compatibility between charging infrastructure and vehicle quality. Allowing for different disutilities from home and away charging allows us to estimate more realistic indirect network effects since we account for the fact that some users never charge away from home.

We also contribute to the literature studying complementary markets and their interactions. This literature has studied complementarities between hardware and software providers of compact discs (Gandal et al., 2000) and video games (Lee, 2013), and between smartphone producers and network operators (Chatterjee et al., 2022), and between content providers and network operators (Jullien and Bouvard, 2022). Benetton et al. (2023) study the impacts of increased electricity demand due to crypto mining on the electricity bills of households and small businesses. Our paper studies market complementarities in the face of widespread electrification and studies environmental externalities on top of product market outcomes. We also propose a model of how individual usage decisions govern the complementarities between the two markets we study.

2 Data and Institutional Setting

2.1 Data sources

We build a comprehensive data set combining sources on car registrations, car usage, charging station entry, and charging station usage in Germany from 2012 to 2021.

Individual car usage data.
We use data on individual car usage from a mobility survey (Mobilität in Deutschland 2017). This survey contains information on whether an individual was at home, using her car, or away from home in 5-minute increments for one day. If the individual reports to be driving, we also observe the distance driven. We also have information on the dwelling type the individual lives in (single-home, two-family home, or apartment building), the income and other demographics, the state of residence, and the degree of urbanization of the user's county of residence. The full survey features 259,509 individuals in 136,357 households. After cleaning and restricting the sample, we end up with 60,414 individuals.

Car registrations.
We use zip-code-level registration data from the German Federal Motor Transport Authority (KBA). This data set contains the new registrations for every model in a given year for private and corporate owners, which we treat as sales. We only focus on registrations of private owners and discard the rest[6]. We define a unique vehicle as the combination of firm, model name, horsepower, engine size, and fuel type.

Car prices and characteristics.
We complement the quantity data with data on list prices (which we treat as transaction prices) and characteristics from the General German Automobile Club (ADAC). Notably, this dataset gives us information on a car's fuel economy, size, vehicle class, and body type. For EVs, it gives us information on the battery size, battery efficiency, and driving range. We match both data sets using our vehicle definition [7], resulting in a data set containing quantities, prices, and car characteristics for 2012 to 2021.

EV charging stations.
Data on charging stations comes from the Federal Network Authority and contains a list of all charging stations. The data set has information on the location, opening date, charging speed, and the number of charging points, giving us information on the number of public charging stations available in every county for each year in our sample.

[6] We do not model the incentives of firms to provide electric company cars and that of car rental and taxi service providers.

[7] We do not match based on engine size for BEVs, a characteristic absent in electric engines.

Charging data.

For all German states, we observe charging at all subsidized charging stations from 2018 to 2023. This data is publicly available from NOW GmbH and the National Centre for Charging Infrastructure. The data lists every charging event at a public charger. It contains the length, start time, end time, and the amount of kWh charged for each charge at a station in the state. We obtain even more detailed data from Stromnetz for the state of Hamburg. These data allow us to see charges at almost all charging stations, regardless of whether the station received subsidies. The Hamburg data includes charges between 2016 and 2021.

Retail electricity and fuel price data.

From the data provider Enet, we obtain information on retail electricity contracts that either allow for BEV charging or are exclusively for BEV charging. We observe pricing details and the zip codes in which contracts are offered for 2012 to 2021. Information on yearly average public charging rates for Germany is obtained from Verivox for 2012 to 2021. Lastly, we observe average gas prices by county for 2012 to 2021 collected by Tankerkoenig, a data provider on gas prices.

Electricity market data.

The Federal Network Agency BnetzA provides data on hourly wholesale prices, hourly renewable generation, and electricity generation units in Germany with a capacity above 10MW. We complement this data with information on the cost factors of individual plants from the Institute of Energy Economics at the University of Cologne (EWI). We collect data on the hourly load in Germany from the European Network of Transmission System Operators for Electricity (ENTSO-e). Data on the average EU ETS price in 2023 comes from the German government environmental agency.[8] We collect all data for 2023.

2.2 User profiles

The individual usage data provides us with many different driver profiles. For illustrative purposes, we employ k-means clustering to collect these individual profiles into five driver types.

[8] `https://tinyurl.com/y3e2s6h9`, last accessed on 08/29/2024.

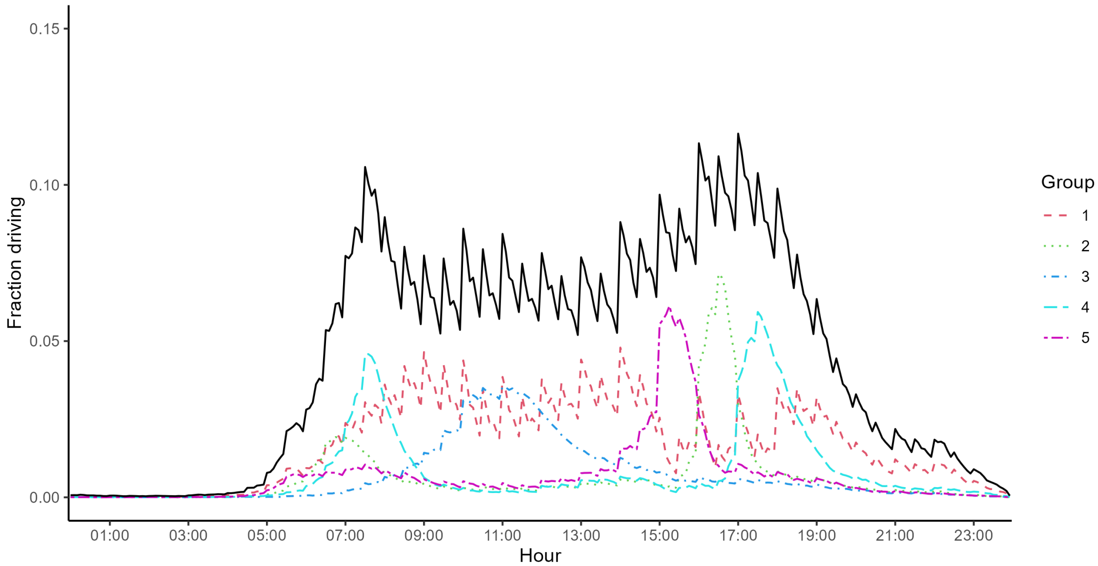


Figure 1: Probability density for different drivers on the road

Figure 1 plots these driver types. For each time of the day, we see the fraction of users within each group on the road. The black line aggregates these driving probabilities up across the five groups. These types pick up typical car usage patterns. Groups 2, 4 and 5 are users who drive in the morning and then again in the afternoon or early evening, likely to commute to and from work. Group 3 mainly drives around lunchtime, while Group 1 scatters their driving across the day. Looking at the black line, we see that almost all driving occurs between 7 am and 7 pm, with almost all cars being idle during the night.

The individual usage data also has information on the type of dwelling the user lives in. We use this information to infer home charging ability. Being able to charge the car at home is often cited as an important consideration in the decision to buy an EV. We assume that users living in one-and two-family dwellings can home charge, whereas larger dwellings (such as apartment buildings) cannot. Together with the information on the degree of urbanization of the user's county of residence, this gives us variation in the share of users with home charging ability across different markets.

Table 1: Number of individuals by group

	Group					**Total**
	1	2	3	4	5	
Size	36,322	6,136	4,647	7,125	6,184	60,414

Table 2 shows the share of users who can home charge across different county types. Only a third of users living in metropolitan areas can home charge, whereas almost three-quarters of users in rural areas can home charge.

Table 2: Home charging availability by county type

	Metropolitan	Urban	Mainly Rural	Rural
Share of home charging availability	0.32	0.68	0.73	0.74

2.3 The evolution of EV sales

Figure 2 plots the share of total sales of different fuel types. Like most EU automobile markets, gasoline and diesel vehicles dominated German sales for decades. From 2016 onwards, alternative fuel technologies have started to gain a non-negligible market share. By 2021, BEVs (electric vehicles without any combustion engine) reached 25% of sales. Together with PHEVS, vehicles with both a plug-in chargeable battery and a combustion engine, the market share reached almost 40%. In this paper, we focus on BEVs, the strongest growing segment and the only vehicles that would lead to full electrification of the vehicle market. We let the EV market start in 2016 and ignore any EV sales before. In doing so, we ignore a minor part of the EV stock. We do not model the internal trade-off between charging and fueling in PHEVs. Grigolon et al. (2024) find PHEVs do not often charge electricity and are mainly used as combustion engines. Moreover, we categorize so-called mild hybrids (combustion engine cars with a complementary battery) as diesel or gasoline engines.

Together with the increase in EV sales, charging stations entered across Germany. Whereas many (mostly very rural) counties had zero charging points in 2016, every county had public charging points in 2021. Most counties had 2-5 public charging points per 10,000 inhabitants by 2021. Some counties had more than 20 public charging points per 10,000 inhabitants.[9] Appendix Figure 3 documents the charging station rollout. The data on public charging stations allow us to build a panel of the cumulative number of charging stations by county and year.[10].

The largest providers of public chargers are electricity generators, supermarkets, local utilities, and specialized start-ups. Nationally, the market is fragmented. In 2021, the 10 largest firms operated around 26% of all public charging points. However, the market is

[9] Tesla operates a private network of chargers, only accessible to Tesla users during our sample period, so they do not qualify as public chargers.

[10] Germany awarded an €8,000 subsidy for the installation and grid connections of a charging station from 2007 onward for charging stations with a Level-2 charging speed up to 22kw. Larger subsidies existed for faster Level-3 chargers. However, most chargers installed until 2021 are Level-2 chargers.

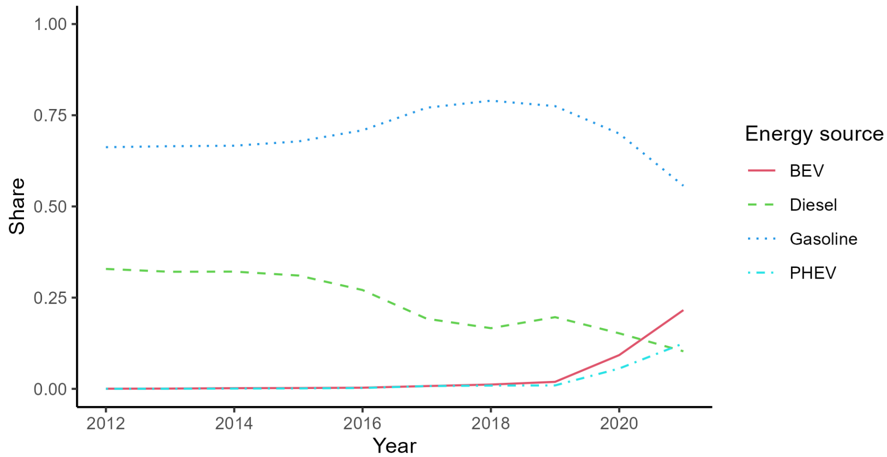


Figure 2: Share of car registrations by energy source

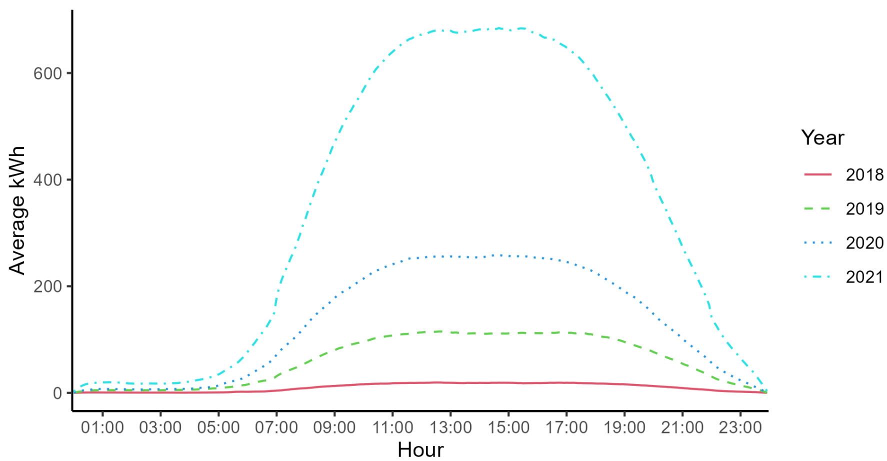


Figure 3: Mean daily public charging at subsidized stations

more concentrated at granular levels, and prices are consistently above residential electricity rates.

2.4 Charging station usage

We visualize the public charging data from the National Centre for Charging Infrastructure for all subsidized public charging stations in all states and for the years 2018 to 2021.[11]

Figure 3 shows the development of mean daily public charging at subsidized charging stations. Public charging has increased drastically following increasing numbers of BEV purchases. Moreover, BEVs sold in later years tend to demand more charging. Whereas

[11]Figure A1 in Appendix A.1 shows the evolution of the number of public chargers per capita by county between 2017 and 2021.

electricity demand from public charging in 2018 is barely visible, it has increased by a factor of around 600 by 2021. Public charging occurs mainly during the middle of the day, while virtually no charging is done at night. This is partly explained by commonly employed night-time charging restrictions of charging station operators.

2.5 Intra-day wholesale electricity prices

Figure 4 shows the yearly average intra-day wholesale electricity price curve for Germany in 2023. There are two price peaks, one in the morning around 8 am and one in the evening around 6 pm. In those hours, demand is high because industrial production is higher than during the night and most households tend to be at home and using their appliances. At the same time, there is less renewable generation (especially solar generation, which tends to be highest in between the two price peaks). This Figure underscores the importance of when electric vehicles connect to the grid: wholesale electricity prices fluctuate by 60% throughout the day, making charging much more costly in some hours than others.

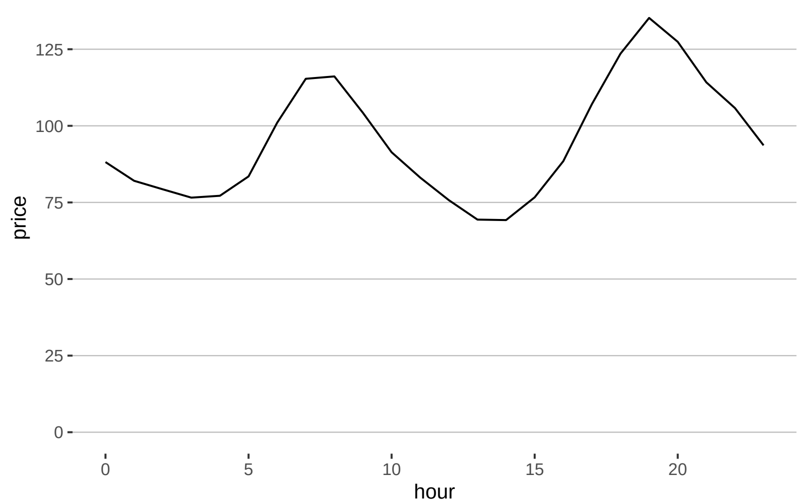


Figure 4: Average hourly wholesale prices in EUR/MWh, 2023

3 Model

We introduce a joint equilibrium model of the new vehicle and electricity market. We specify vehicle demand and supply and electricity demand and supply. Both markets are connected through the electricity demand from electric vehicles, which we obtain from a charging model with rich individual heterogeneity. The charging model is a micro-founded model of optimal charging behavior. A related approach is taken by Butters et al. (2021), who model the charging behavior of commercial battery owners. We first present the charging model before describing the vehicle market, the electricity market, and the equilibrium. We also model the importance of charging stations, but we do not model them as making strategic responses.

3.1 Notation and Timing

We consider a setting where consumers buy a vehicle with a lifetime T. The vehicle lifetime can be split into identical sequences running from $s = 1$ to S. For example, a vehicle has an expected lifetime of 15 years, and we consider each 5-minute interval in the lifetime to be a sequence. We use the notation $.(s)_{s=1}^{S}$ for sequences.

We define the new vehicle market as a combination of a calendar year t and a region g. A region is a state-county combination, where the county type can be metropolitan, urban, mainly rural, or rural, as defined by the Federal Office for Building and Regional Planning. The electricity market takes place in every sequence of s, and we define the geographical market for electricity as the whole of Germany. The endogenous variables in the model will be vehicle prices and energy prices. Each calendar year has J vehicles on sale, and their prices are p_j. We use notation $\mathbf{p}$ to define the vector of all prices in a market. Energy prices are set for each hour of the day s. There are three energy price sequences: wholesale prices $(p_s^w)_{s=1}^{S}$, retail prices $(p_s^h)_{s=1}^{S}$ paid for electricity consumption at home, and charging station prices $(p_s^a)_{s=1}^{S}$ paid by consumers charging their EV away from home. Our model is a joint equilibrium model of vehicle prices and electricity prices.

3.2 Charging Model

We model a dynamic finite-horizon cost minimization problem over the sequence S in which an individual chooses whether or not to charge their EV in each period s. The cost minimization is constrained by the electricity demand required to fulfill driving needs and by battery limits.

The main role of the charging model is to connect the vehicle market with the electricity market. Electricity expenses affect vehicle demand as an operating cost, but in turn, the electricity generated by vehicle demand affects the electricity market equilibrium. Individual heterogeneity is key to modeling this link because different individuals charge at different times, and there is a large intraday variation in electricity demand and supply. Therefore, we focus on a charging cost-minimization problem with detailed intraday heterogeneity. The problem is specific for an individual travel profile w_i, a vehicle j, and a market gt. We start by describing each of these three determinants of the charging problem.

Individual travel profile We define an individual i to have an intraday car travel profile $w_i(s)_{s=1}^S$. The travel profile consists of three sequences: an indicator h_s determining home status in each s, an indicator r_s taking the value one if the individual is driving in s, and a sequence of positive integers m_s denoting the distance traveled in each s. By definition, the distance traveled is zero when the individual is not traveling. Together, these three variables determine the location (home, on the road, away from home) and the distance traveled over the sequence S. The sequence $w_i(s)_{s=1}^S$ is a multidimensional object capturing location and travel information. We define w_{is} as a vector containing the sequence values at s and r_{is}, h_{is}, and m_{is} to capture travel status, being at home, and distance.

Car features The relevant features of a car j are the battery size R_j in kWh and the per-kilometer electricity consumption Kw_j. These are the two only attributes affecting the charging problem; we account for many other attributes in vehicle demand.

Market features The solution to the problem depends on the geographical location g of a potential buyer and time period t. Electricity prices might vary across regions and time periods. For example, real-time electricity pricing makes the charging problem depend on the price in each of the s intervals. We denote p_{sgt}^h as the residential electricity rate at interval s in market gt. Likewise, a consumer faces charging station electricity prices p_{sgt}^a when purchasing electricity away from home.

Lastly, we define the charging speed C as the kWh charged in a period s. We assume that it is constant. The model could be extended with a location, vehicle, or time-varying charging speed.

Charging Problem The charging problem is specific for each travel profile-vehicle-market combination. For exposition, we drop all but the period subscript s. In each period s within the time horizon S, an individual can decide to charge her EV or not. This binary decision is captured by the variable c_s. The decision affects a state variable B_{s+1}, the battery charge level in kWh. The state variable transitions in the following way:

$$B_{s+1} = \underbrace{\mathbb{1}\{r_s = 0\}(B_s + c_s \times C)}_{\text{Charging or Idle}} + \underbrace{\mathbb{1}\{r_s = 1\}(B_s - m_s \times Kw_j)}_{\text{Depleting Battery}}.$$

This equality holds for all $s = \{1, ..., S\}$. If the travel profile w_{is} describes individual i to be driving in period s, then there is no choice, but the battery depletes by $m_s \times e$, which captures the car's energy consumption for that trip. If the travel profile describes the individual not driving in s, then she can either charge $c_s = 1$ or not. The battery level stays the same when not charging and increases by E if charging.

The technical constraints on the battery level are that the charging level cannot exceed the battery size R of the car, and it cannot be negative. We formalize this as:

$$R \geq B_s \geq 0 \quad \forall s.$$

Let us now define the cost minimization problem. The state variables of the problem are $\{s, B_s, w_{is}\}$. For an individual without access to home charging faces, $l = 0$, the problem is:

$$V_s^{l=0}(B_s) = \min_{c_s} \left[\mathbb{1}\{r_s = 0\} \times p_s^a \times c_s \times \min\{C, R - B_s\} + V_{s+1}^{l=0}(B_{s+1}) \right], \tag{1}$$
$$\text{s.t. } R \geq B_s \geq 0 \quad \forall s$$

The program captures the idea that individuals are forward-looking: they consider their future driving needs and electricity rate differences when deciding their charging. Whenever they are not driving, they face the choice of charging or not charging. When charging they face a monetary cost defined by $p_s^a \times \min\{E, R - B_s\}$. This cost captures the maximum kWh the car recharges within one period, which is capped by the battery capacity.

We define the minimization problem for an individual with access to home charging, $l = 1$, as:

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

where h_s is used to determine if i is at home or not. This program is similar to (1) in the sense that there is only a decision of charging or not if the individual is not driving. However, when not driving in a given period s, the individual might be at home. If they are at home and charge, they face the cost derived from the price p_s^h. If away from home, they face the public charging price p_s^a.

We define the solution of the charging problem for each individual-vehicle-market combination as $c^*_{ijgt}(s)_{s=1}^S$, which is the cost-minimizing sequence of charging decisions. The solution allows us to construct several variables useful in the vehicle and the electricity market model. First, the optimal sequence gives rise to an electricity load sequence for every $ijgt$ profile: $e^*_{ijgt}(s)_{s=1}^S$. Because we know the home status of i, we can split the load profile into residential charging $\boldsymbol{e}^{h^*}_{ijgt}$ and station charging $\boldsymbol{e}^{a^*}_{ijgt}$. The load curves are specific for each vehicle j, so we need to specify a demand model that informs us how the choice of j changes with energy expenses. Therefore, we define three more variables to specify demand. The variable $A_{ijgt}^{l_i=0} = \sum_{s=1}^{S} \mathbb{1}\{l_i = 0\}(e_{ijgt}^{a*}(s)p_{gt}^{a}(s))$ defines the monetary energy expenses from optimal charging for vehicle j when i cannot charge at home. The expense is derived from the optimal charging patterns by multiplying electricity demand at each s with charging station prices. Similarly, we can define two variables $H_{ijgt}^{l_i=1} = \sum_{s=1}^{S} \mathbb{1}\{l_i = 1\}(e_{ijgt}^{h*}(s)p_{gt}^{h}(s))$ and $A_{ijgt}^{l_i=1} = \sum_{s=1}^{S} \mathbb{1}\{l_i = 1\}(e_{ijgt}^{a*}(s)p_{gt}^{a}(s))$ for individuals that can charge at home where the first one is the energy expense from home charging and the latter one is that of public charging for each combination $ijgt$.

The charging model gives us another piece of information as it restricts the choice set of cars for certain individuals. Some individuals might have exogenous driving profiles that make it impossible for them to satisfy their driving needs with a certain EV without violating the technical constraints of a positive battery level at all times. This captures the fact that EVs need much more time for recharging than cars with internal combustion engines, such that certain individuals would not consider buying an EV. We define the individual choice set of i as χ_i.

3.3 Vehicle Market

Vehicle Demand The exposition follows the BLP model, Berry et al. (1995), and extends it to incorporate the solution of the charging model.[12] An individual i in geographical market g in a year t derives indirect utility from a car j that is in χ_i defined below:

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

ξ_{jgt} are car, engine type and market fixed effects and ϵ_{ijgt} is i.i.d. Type I extreme value distributed. Preferences for attributes x_{jgt}^{k} and car prices p_{jgt} are random coefficients based on observed and unobserved heterogeneity. Given that we observe individual driving patterns, we can derive the individual fuel cost G_{ijgt}^{ICE} for internal combustion engine cars. This variable is based on an average fuel price in a given market, the fuel consumption of the car, and the individual's aggregate driving need over the period S so that the parameter is directly comparable to the electricity costs of EVs. While this adds interesting observed individual heterogeneity, the more crucial element is captured in $G_{ijgt}^{EV}\gamma^{EV}$, which adds to the indirect utility if car j is an EV.

[12]Using an optimal decision as a demand shifter in a choice model is similar in spirit to Jia Barwick et al. (2022b) who plug optimal travel patterns in a location choice model.

We define EV electricity expenses in the following way:

$$\begin{aligned} G^{EV}_{ijgt}\gamma^{EV} &= \mathbb{1}\{l_i = 0\}\left[(\gamma^a + \gamma^{ad} d_{gt}) A^{l_i=0}_{ijgt}\right] \\ &\quad + \mathbb{1}\{l_i = 1\}\left[(\gamma^a + \gamma^{ad} d_{gt}) A^{l_i=1}_{ijgt} + \gamma^h H^{l_i=1}_{ijgt}\right]. \end{aligned}$$

The first term is the disutility from monetary electricity expenses at charging stations from individuals not having the option to charge from home, and the second term is the disutility from expenses by individuals who can charge vehicles at home.

In total, there are four parameters capturing the disutility from operating expenses: γ^{ICE} and $\gamma^{EV} = \{\gamma^a, \gamma^{ad}$, and $\gamma^h\}$. These terms are all monetary expenses and rational consumers could be assumed to have the same value for a euro spent on a vehicle or a euro in the net present value of fuel costs. As such, the γ^{ICE} and γ^{EV} could be interpreted as capitalization parameters that translate the expenses over S into their net present value over the vehicle lifetime (which includes many S periods). However, there is a large literature showing that consumers do not value vehicle price and future fuel costs equally, see Hausman (1979), Busse et al. (2013), Allcott and Wozny (2014), and the subsequent literature. We follow this literature but additionally allow the valuation of electricity expenses to differ from the valuation of fuel costs. We do this because electricity prices might not have the same salience as fuel prices, and the fueling time and convenience costs might differ between oil fuels and electricity. Existing evidence shows that consumers do not value both equally; see Bushnell et al. (2022).

Our specification further allows for different valuations for residential electricity expenses (γ^h) and charging station expenses (γ^a, γ^{ad}). Consumers might experience more disutility from charging station expenses compared to simply plugging in at home. Furthermore, the disutility from charging station expenses might decrease when there are more chargers in the region, decreasing the risk of congestion at the station and the distance needed to travel to a charger; this is captured by allowing the disutility from charging station charging to vary by d_{gt}.

The EV-specific component of the indirect utility has several important economic features. First, it allows us to incorporate to which extent home and public charging differ in their effect on the purchase decisions of heterogeneous individuals. This aspect enters in a micro-founded way where we use the charging model to link individual travel profiles, EV attributes, and market conditions in terms of electricity prices and charging networks. This contributes to the existing EV literature, see for example Springel (2021) and Remmy (2023), that specifies the indirect utility to be a function of EV attributes without distinguishing between home and away charging and without linking EV attributes to the battery charging problem. We further refine previous approaches. In addition to including public charging station density as a common utility shifter, we also include it as a shifter that affects the expense disutility of individuals who cannot charge at home while not affecting home charging expense disutility.

With the definition of the indirect utility and the assumption of type I extreme value distribution on ϵ_{ijgt}, we can derive individual choice probabilities $\sigma_{ijgt}(w_i(s)_{s=1}^S, z_i, \nu_i)$ which can be aggregated to model vehicle sales q_{jgt}:

$$q_{jgt}(\mathbf{p}, (p^a)_{s=1}^S, (p^h)_{s=1}^S) = \iiint L_{gt}\sigma_{ijgt}(\mathbf{p}, w_i(s)_{s=1}^S, z_i, \nu_i) \; dF_\nu(\nu_i)dF_z(z_i)dF_{w_i}^g(w_i), \tag{3}$$

where $\sigma_{ijgt} = 0$ if $j \notin \chi_i$ and L_{gt} is the potential market size in each gt. The random variable ν_i captures unobserved heterogeneity, and z_i are observed consumer demographics. This expression accounts for individual choice sets χ_i and integrates over the distribution of travel profiles w_i specific to geographical regions. Vehicle quantities are a function of the three prices: vehicle prices p_j and residential $(p^h)_{s=1}^S$ and charging station $(p^a)_{s=1}^S$ electricity price sequences through the electricity expense terms associated with travel profile $w_i(s)_{s=1}^S$ optimal charging for vehicle j.

Vehicle Supply We assume the set of vehicles of each manufacturer f to be J_f and to be fixed. Notice that most manufacturers own both EVs and combustion engines. Businesses stealing from their combustion segments are important to determine manufacturers' strategic EV pricing. Firms annual profits are given by:

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

where mc_j is the marginal cost of vehicle j, q_j is sales quantity, and $\boldsymbol{p}$ is a 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 $p_{jt} + \lambda_{jt}$ for selling vehicle j, and consumers pay pjt, the sticker price net of the subsidy. We assume prices and marginal costs are fixed across regions g in a given year. Assuming Nash Bertrand competition, we obtain the first-order condition of profits with respect to prices. Let Ω be the ownership matrix, where the element Ω_{jh} indicates whether the same firm sells product j and product h. Let $D(\boldsymbol{p})$ be a matrix whose element $D_{jht} = -\sum_g \frac{q_{hgt}(\boldsymbol{p})}{\partial p_{jt}}$. Then, the first-order condition of the firms' maximization problem is:

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

where $\boldsymbol{q} = \sum_g q_{jgt}$ is the vector of vehicle quantities, and $\odot$ is the element-by-element matrix multiplication operator.

3.4 Electricity market model

Electricity demand We assume that the electricity market is characterized by an inelastic base load $E_t^B(s)$. This baseload presents German electricity demand before any consumption of electric vehicles in period t. Total electricity demand in every time interval s is equal to the sum of the base load and the implied electricity demand from the vehicle model. In every given s, the following holds:

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

$$E_{ts}^{EV} = \sum_i \sum_j \sum_g (L_{gt}\sigma_{ijgt}e_{ijgts}^*), \tag{7}$$

we obtain the electricity demand by the sum of the baseload and the implied electricity demand from the vehicle choices (which depends on the solution of the charging model). These equations hold at every s, so we obtain the sequence $(E_t^D(s))_{s=1}^S$ describing the demand profile over the period S. Vehicle price changes, for example, from subsidies, change the implied electricity demand through (3) entering the electricity demand. Electricity prices affect the electricity demand sequence through the market shares, which are a function of the terms A_{ijgt} and H_{ijgt}, and through the optimal solution for charging, $\mathbf{e}_{ijgt}^*$.

Electricity supply Electricity is supplied by generators k that can each produce an amount of electricity $e_{kt}(s)$ at a marginal cost mc_{kt}. For renewable energy suppliers, the amount of electricity produced varies across the time of the day s depending on wind and sun conditions. Other generators, such as coal or gas, can offer a constant amount of electricity at each point of the day, and we abstract away from ramp-up costs. We order the generators by increasing marginal cost mc_{kt} such that $k = 1$ has the lowest and $k = K$ has the highest marginal cost. We define a sequence $(a_{kt})_{k=1}^K = (\sum_{j=1}^k e_{jt})_{k=1}^K$ and set $a_{0t} = 0$. The merit order curve is a step function:

$$M(x) = mc_{kt} \text{ for } x \in (a_{k-1t}, a_{kt}]$$

for all $k = 1, ..., K$. Given this merit order, we can define the optimal dispatch. We assume there is no network congestion so that all generation can be flexibly dispatched to any region g within the market. Furthermore, we ignore exports and imports and abstract away from generator market power.[13] We assume optimal dispatching so that the network operator assigns generation to the least cost operators until demand is met. All dispatch plants supply at full capacity except for the marginal plant, which supplies the remaining energy needed for balancing. We define E^G_{st} as the total energy dispatched from generators. The equilibrium price is defined as $p^w_{st} = mc_{k^*t}$ where $\{k^* | \sum_{k=1}^{k^*-1} e_{kst} < E^D_{st} \;\&\; \sum_{k=1}^{k^*} e_{kst} \geq E^D_{st}\}$. We assume there is a fixed mark-up to link the wholesale price to the retail and charging station prices. In a market without retail and charging price variation over S, we obtain:

$$p^a_t = \mu_a + \frac{\sum_{s=1}^S p^w_{st} E^G_{st}}{\sum_{s=1}^S E^G_{st}}$$
$$p^h_t = \mu_h + \frac{\sum_{s=1}^S p^w_{st} E^G_{st}}{\sum_{s=1}^S E^G_{st}}.$$

We describe below how we derive time-varying retail and charging station prices in the counterfactuals.

3.5 Equilibrium

The equilibrium of the vehicle and electricity market is a set of J vehicle prices $\boldsymbol{p}$ and a sequence of S electricity prices $(p^G(s))_{s=1}^S$ such that:

1. The electricity load sequence $(e^*_{ijgt}(s))_{s=1}^S$ for each individual, vehicle, and market combination $ijgt$ is the solution of the battery costs minimization problem in (1) or (2) and results in electricity expenses $A^{l_i=0}_{ijgt}, A^{l_i=1}_{ijgt}, H^{l_i=1}_{ijgt}$

2. The vehicle market is determined by the demand equation (3) and firms set vehicle prices $\boldsymbol{p}$ following the first-order condition in (5).

3. Electricity demand is given by equation (6) and supply determined by optimal dispatch, and the market clears at every st so that $E^G_{st} = E^D_{st}$ resulting in $p^w_{st}, p^a_{st}, p^h_{st}$.

These conditions specify the equilibrium conditions for the vectors of electricity prices, vehicle prices, and resulting electricity and vehicle quantities. To gain intuition, we describe the equilibrium effects of a subsidy for EV purchases. A subsidy decreases the price of electric vehicles, leading to more EV sales, which in turn increases electricity demand. Depending on the changes in demand, different individuals with travel profiles $w_i(s)_{s=1}^S$ will cause a change in the specific sequence of the load curve $E^{EV}_t(s)_{s=1}^S$. This, in turn, changes the electricity

[13] Imports could be easily introduced in the model by representing them as an additional generator in the merit order. This necessitates an assumption about the marginal costs of imports.

prices because the demand might cross the merit order at a different point. New electricity prices imply that consumers incur different electricity expenses to charge and update their battery charge cost-minimizing solution.

4 Estimation

This section discusses how we estimate the charging model, the demand model for cars, and the electricity market model.

4.1 Solution method for the Charging Model

We obtain individual travel profiles $(w_{is})_{s=1}^{S}$ directly from the individual car usage survey data. We restrict individuals from the survey to those owning a car and limit the sample to weekdays. To solve the dynamic charging model, we construct a horizon S of 14 days by repeating the observed daily travel profiles 14 times. For each individual, the survey identifies the geographical market g. We observe the battery size R_j and per-kilometer electricity consumption e_j for each BEV in the data from the car registration and characteristics data. We assume a uniform charging speed equal to 11 kW. Lastly, we use the data on residential and public charging retail electricity rates to construct average regional electricity rates p_{gt}^{h} and p_{gt}^{a} per year. Notably, in all markets, the electricity rate for public charging is strictly higher than that for home charging. Germany employs flat electricity rate contracts, and charging station prices do not vary across the day. Therefore, the observed prices are not s-specific and hence do not vary intraday. One of our main counterfactuals studies intraday electricity price variation.

The lack of intraday electricity rate price variation causes a multiplicity issue when solving the dynamic charging model. Without price variation, an individual with a certain EV will be indifferent between two different charging profiles $c_{ijgt}^{1}(s)_{s=1}^{S}$ and $c_{ijgt}^{2}(s)_{s=1}^{S}$ that imply the same amount of home and away charging because the cost will be equivalent. To solve the multiplicity issue, we make behavioral assumptions on the timing of the charges.[14]

When electricity rates are flat, we first solve for the expenses of every travel pattern-by-vehicle-by-region combination. If an individual can home charge, we first check if the EV is compatible with the travel profile when only relying on home charging. Because home charging is strictly cheaper than charging at a station, the cost of charging is simply the electricity rate multiplied by the electricity needed to satisfy the driving profile. If charging

[14]Note that the multiple solutions all have equivalent costs but imply charging at different times s. Therefore, selecting the solution profile matters for the electricity market but not directly for the vehicle market (which only depends on expenses).

at home is insufficient to satisfy driving needs, we check if the driving need can be fulfilled by charging at home and a charger when the driver is away from home and not driving. We employ a nighttime restriction for charging at stations, not allowing charging between 11 pm and 6 am.[15] If the electricity from both home and station charging is sufficient, we include the EV in the individuals' choice set χ_i. The cost equals the sum of the home charging and station charging expenses. If both home and station charging are insufficient to satisfy the travel profile, we exclude the EV from the choice set. Note that EVs with larger batteries are more likely to be included in the choice set. Finally, if an individual cannot home charge, we repeat the same steps, letting her recharge every period she is not driving (outside of the nighttime charging restriction). If this charge does not cover the driving needs, the EV is excluded from the choice set. Consumers unable to home charge will thus face a choice set with fewer EVs, especially if they drive a lot during the day. Otherwise, the cost of station charging is taken as the electricity expense.

Finally, the charging profile can be distributed across several periods s whenever electricity rates are flat because multiple charging sequences result in the lowest cost for individuals. We use two different solutions for the multiplicity problem. In the first solution, we distribute all charging equally across all available periods. This would mimic a random charging decision by consumers over the periods s. The aggregated charging patterns we obtain match those we observe at charging stations reported in Figure 3. In the second solution, we adjust the home charging pattern to align with evidence on behavior presented in Bailey et al. (2024). We assume an "arrive-at-home and plug-in" behavior for home charging. Charging upon arrival at home entails individuals plugging in their EV after their last trip of the day and charging electricity until the EV is fully recharged. We keep random charging at stations.[16]

In counterfactuals with s-specific electricity rates, there is no multiplicity issue. In such case, we solve the dynamic model by backward induction and obtain a unique solution $c^*_{ijgt}(s)^S_{s=1}$ that determines expense at home and chargers and determines intraday electricity load profiles.

From the solutions; we can derive $A^{l_i=0}_{ijgt}$, $A^{l_i=1}_{ijgt}$ and $H^{l_i=1}_{ijgt}$ and determine χ_i. We do this for each individual-EV-region combination, resulting in more than eleven million electricity cost estimates for BEVs. Depending on the behavioral assumption, we also know their individual

[15]This restriction is confirmed in the data. Charging stations prohibit overnight parking, and in the charging station data, we indeed observe that there is almost no charging at night.

[16]For instance, if a consumer arrives at home at 6 pm, leaves at 8 am the next day, and needs to charge 10kWh, which could be done in 2 hours, we do not know when exactly this consumer charges. In the first solution, we distribute the 10kwh equally over each 5-minute interval between 6 pm and 8 am. In the second solution, the consumer charges between 6 pm and 8 pm.

electricity consumption at home and at chargers. We also construct the fuel cost from using an ICE car G^{ICE}_{ijgt}) by multiplying the fuel price with the fuel consumption needed to satisfy the kilometers traveled for each travel profile and vehicle. We use regional fuel prices to compute fuel costs.

4.2 Demand Estimation

For the demand model, we extend the estimation method of Berry et al. (1995) to our setting. We construct s_{jgt} as the number of car registrations divided by potential market size L_{gt}. We obtain the potential market size from the survey responses on total car ownership. We assume households keep vehicles for seven years and derive the potential market size for new vehicles in gt as the total number of cars owned in gt divided by seven.[17]

There are two endogeneity concerns in the demand specification, which we address by choosing suitable instruments. First, firms set car prices with knowledge of unobservable product characteristics leading to the endogeneity of the car price. Second, the charging station density d_{gt} depends on BEV demand, creating a potential endogeneity problem due to an indirect network effect. Finally, we must also define moments to identify the nonlinear parameter vectors γ^{ICE} and γ^{EV}.

We construct the following instruments. First, we compute differentiation IVs for horsepower and fuel economy; see Gandhi and Houde (2019). We complement this with the PPP-adjusted exchange rate of Germany with the production country of each vehicle interacted with the vehicle's weight. This instrument is similar to the one used in Grieco et al. (2024). We also include a cost shifter by interacting the vehicle weight with a yearly metal price index. Therefore, we have both instruments that shift markups and costs. We use construction land prices to instrument the charging station density, varying by geographical market and year. We also use cumulative state-level subsidies for the construction of public charging stations.

A key set of parameters we need to identify are the usage cost valuation parameters and the BEV-specific dummy and attributes. We identify the BEV dummy from variation in market shares of BEVs vs combustion cars across markets. Variation in market shares across different BEVs with different range helps us identify consumer valuation for range.

To identify the usage cost parameters, we first rely on variation in market shares and fuel/electricity costs across markets. Second, to help identify the nonlinear parameters, we compute proxies to the "most powerful" instruments defined in Lesellier et al. (2023). We

[17]On average, consumers in Germany hold on to their new car for around seven years. Vehicle lifetime is 14 years on average in the EU; when purchasing vehicles, consumers care about the lifetime expenses, which affect the vehicle's resale value.

add the quartiles of $A^{l_i=0}_{ijgt}$, $A^{l_i=1}_{ijgt}$, $H^{l_i=1}_{ijgt}$ and fuel costs to the instrument set, defined as $A^{l_i=0}_{(i=25th)jgt}$ etc. These instruments capture the shape of the distribution of electricity and fuel expenses across individuals.

An important output of the estimated model is the individual charging profiles. To make the model match observed charging in the data, we match an additional moment equal to the daily average charging at stations in each five-minute interval by state and year. This moment is crucial to match not only public but also home charging because the two must add up to equal the total electricity demand from EVs. We observe aggregate station charging e^a_{Gts} at the state level G at 5-minute intervals and sum over the regional-specific model-implied charging to match both:

$$e^a_{Gts} = \sum_{g \in G} \sum_{k=2016}^{t} \sum_{j \in EV} \sum_{i \in gt} e^{*a}_{ijgks} \sigma_{ijgk} + \eta_{Gts}.$$

There are multiple important points. The observed public charging on the left-hand side is at the state level G and captures the charging of the stock of BEVs sold in years prior t. On the right-hand side, our model predicts charging demand for each individual at the regional level for newly sold BEVs in t, i.e., the flow of BEVs. Therefore, we sum across regions in each state, previous EV sales (flows), and individuals to equate both measures. Any error between the model implied and observed station charging is collected in η_{Gts}.

In practice, we restrict ourselves to matching the public charging demand for 2019 and 2021. The 2018 data is incomplete (the data collection started in that year), and in 2020, we observe a much lower charging demand driven by movement restrictions during the COVID pandemic. The travel profiles are fixed in time as we do not observe time-use surveys in multiple years, and we cannot explain the change in travel behavior and charging in 2020. The station charging data is limited to subsidized charging stations. We observe charging at all stations in the state of Hamburg and use that data to scale the observed data at the subsidized stations to all charging stations. We further adjust for the fact that our model predicts only charging from private EV owners but the charging data is based on all EV owners. We detail this in Appendix A.2.

We have two moment conditions: the aggregate market share moment $E(\xi_{jgt} z_{jgt}) = 0$ and the state-level 5-minute station charging moment $E(\eta_{Gts}) = 0$ capturing the matching of observed public charging demand. We denote the sample analogs of these moments as G^1 and G^2 and stack them in G. This leads to the following GMM objective:

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

where W is a consistent estimator of the inverse of the asymptotic variance-covariance matrix of the moments, note that the weighting matrix is block diagonal as we match two different samples.

4.3 Empirical model of the Electricity Market

We interact the hourly net load with a merit order model to obtain the equilibrium wholesale price for each of the 8,760 hours of the year. We use 2023 as our reference year rather than 2020 or 2021 because of the Covid-19 pandemic and the large gas price fluctuations caused by Russia's invasion of Ukraine.

Our model is an extension of the Merit Order Tool provided by EWI (for documentation of the tool, see EWI, 2024). We obtain the net load by subtracting realized renewable generation from the hourly load. We estimate every thermal generation unit's margin cost in the Geman electricity market to build the Merit Order. The marginal cost of generator k is a function of fuel price, the emissions factor, other variable costs, and a unit's efficiency and is given by

$$c_k = \frac{\textit{fuel price}_k}{\textit{efficiency}_k} + EUA \times \frac{\textit{emissions factor}_k}{\textit{efficiency}_k} + \textit{variable costs}_k,$$

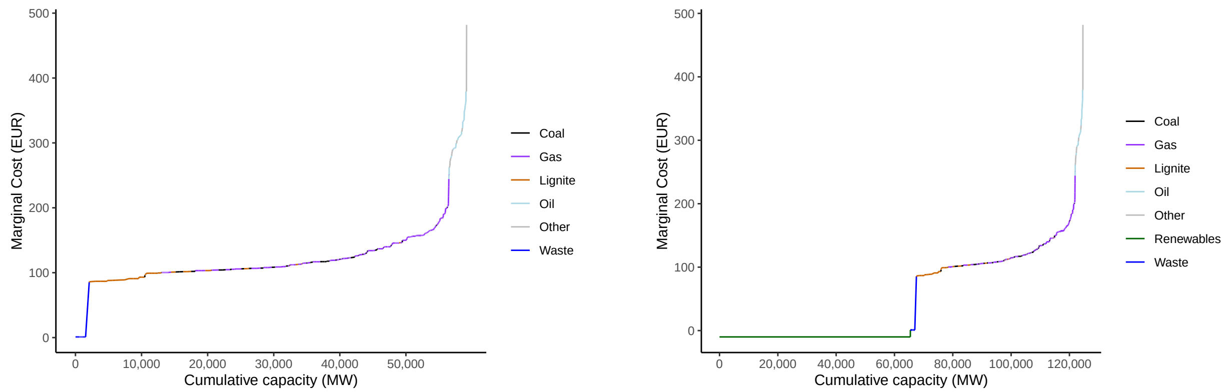
where the fuel price comprises transport costs, and EUA denotes the EU Carbon Permit price, which we set to €83.66 per t/CO2, the average price for 2023. We set the capacity of each plant to be

$$e_k = e_k^{gross} \times \textit{unavailability}_k,$$

where e_k^{gross} is the gross generation capacity of generation unit k and $\textit{unavailability}_k$ is the unavailability rate of plant k, defined as the average amount of time that a generation unit k is not online due to maintenance or unanticipated issues. Table A1 in Appendix A.1 shows the assumed values to construct marginal cost estimates.

There are some hours when renewable generation is sufficient to meet the load. In those cases, we assume the wholesale price equals €- 10/MWh. We do so because negative bidding is common in such hours since renewable generation units receive generation subsidies, making it profitable to supply electricity even at negative prices.

Our model makes several simplifying assumptions. We abstract away from ramp-up costs. Ramping up generation can be costly and lead to higher marginal costs during ramp-up. Also, we do not model imports and exports and treat Germany as an autarky. Finally, we do not consider transmission constraints that arise when electricity is demanded far from where it is generated. The transmission lines connecting the demand and supply areas do not have sufficient capacity.



No renewable generation | Maximum observed renewable generation

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

Figure 5 shows two merit orders, one without any renewable generation (left panel) and one with the highest amount of renewable generation that we observe in 2023 (right panel). The left panel shows that lignite plants come online first (except for a small amount of waste-based electricity production). Once their capacity is exhausted, a mix of hard coal and gas plants come online. Hard coal tends to have a lower marginal cost but is also more emissions-intensive, making its marginal cost comparable to gas plants due to the CO2 price (Figure A2 in Appendix A.1 plots the distribution of marginal costs by generation type). The increase in marginal cost accelerates as the most expensive gas plants are being brought online and then skyrockets towards €500/MWh as oil peakers need to be dispatched. The right panel shows that renewables can double the available capacity in the most favorable hours. When renewable generation is high enough to meet electricity demand by itself, wholesale prices are low, and electricity is zero-emission. When renewables can not cover the market by themselves, we take a discrete jump towards around €100/MWh as thermal units need to come online.

5 Results

5.1 Charging Model Solution

Table 3 presents the average daily cost of charging for EVs and refueling for combustion vehicles in our data. These are unconditional cost averages over all travel type-by-vehicle combinations without considering vehicle choice. About one percent of all individuals have

Table 3: Unconditional average daily costs from fueling/charging in Euros

	Fuel Expense	Public charging		Home charging
	G^{ICE}	$A^{l=0}$	$A^{l=1}$	$H^{l=1}$
All cars:				
Mean	€2.71	€1.95	€2.43	€1.15
St. Dev.	€3.87	€2.25	€3.02	€1.28
VW up!:				
Mean	-	€1.43	€1.81	€0.88
St. Dev.	-	€1.50	€2.04	€0.87
Tesla Model Y:				
Mean	-	€2.88	€4.09	€1.67
St. Dev.	-	€3.23	€5.57	€1.80
VW Golf super:				
Mean	€2.65	-	-	-
St. Dev.	€3.52	-	-	-
VW Golf diesel:				
Mean	€2.02	-	-	-
St. Dev.	€2.69	-	-	-

at least one BEV that is not in their choice set. BEVs in our sample can technically satisfy almost all weekly travel profiles in our data. Combustion technologies cost on average €2.71 per day with a substantial standard deviation of 3.8. The variability comes from vehicles with different fuel economy; we show a VW Golf Super costing €2.65 and a VW Golf Diesel costing €2.02, but also from mileage differences between travel profiles. The average expenses for electricity at home are only €1.15, showing that driving an EV is cheap when one charges at home; charging a Tesla Model Y at home is cheaper than operating a VW Golf diesel. Charging at stations is considerably more expensive, driven by the high mark-up of charging stations above retail prices. Charging a Tesla Model Y at charging stations is more expensive than operating a VW Golf. The expenses for away charges for consumers that charge at home, $A_{ijgt}^{l_i=1}$, are even higher. Outlier drivers explain this; only very high-mileage consumers find home charging insufficient, and these drivers also need to charge a lot at stations. We find below that these drivers are unlikely to buy EVs.

5.2 Demand Estimates

Table 4 presents demand estimates. The mean utility includes the volume, weight, horsepower, the number of doors, and consumer prices (accounting for subsidies). For BEVs, we add the range and the charging station density, defined as the logarithm of the number of charging stations plus one. We add fixed effects for fuel types (diesel, PHEV, BEV, and HEV), car class, body type, manufacturer, state, and a time trend. We find consumers like more powerful and larger cars. The mean price elasticity is very much in line with previous estimates from the same region and sample period (see Remmy, 2023; Alé-Chilet et al., 2021; Miravete et al., 2018). We find that consumers' preferred fuel type, conditional on all controls, is HEV before gasoline (the reference) and PHEV. German consumers dislike diesel and especially BEVs. Range and charging station density have the expected positive sign so that BEVs are considered more when batteries improve over time and when charging stations become more prevalent in later years.

The fuel expense parameters are γ^a, γ^{ad}, γ^h and γ^{ICE}. Table 4 Column 'Only G^1' includes only the moments based on sales defined in G^1. In the next Column, we include G^2 and additionally match the observed station charging. We find that consumers strongly dislike expenses at charging stations, but γ^{ad} is positive, implying that denser charging station networks reduce the negative disutility from charging. We also find that consumers dislike electricity expenses at home, γ^h, but less so than the disutility associated with combustion fuel γ^{ICE}. Notice that the additional moment G^2 is important to scale these parameters, the parameters related to charging double in absolute size because of the additional moment. Without the additional moment there is only variation in the different driving profiles and EV market shares to estimate which use profiles buy EVs. The additional moment forces the model to assign different disutilities of home and away charging so that we match the observed amount of charging in each market.

The model without the moment G^2 predicts that consumers without access to home charging make up 30% of BEV buyers and that these drivers commute 13km per day. This leads to an electricity demand that is too high when we do not impose G^2. When the model matches observed charging, the estimation procedure increases the disutility from charging at stations. Away chargers, especially high-mileage types, buy fewer EVs. We find they now represent only 27% of EV buyers driving on average 8.5km when adding G^2, while the share of home chargers increases to 72% but they also are lower mileage types driving on average 19km per day.

The charging model and the demand estimation results combined enable us to predict charging at home and stations throughout the day. Figure 6 plots the average daily predicted

Table 4: Demand Estimation

	Only G^1		G^1 and G^2	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
Mean parameters:				
price	-0.0510	0.0044	-0.0552	0.0043
bev	-1.7181	0.0879	-1.3045	0.0864
range	0.0016	0.0002	0.0015	0.0002
charging station density	0.4981	0.0530	0.6333	0.0515
phev	-1.2411	0.0188	-1.2649	0.0187
diesel	-0.8527	0.0134	-0.8464	0.0134
hev	-0.6385	0.0264	-0.6346	0.0263
volume	0.1557	0.0059	0.1585	0.0059
weight	-0.0754	0.0658	-0.0142	0.0655
horsepower	-0.0021	0.0007	-0.0014	0.0007
doors	-0.1009	0.0075	-0.0977	0.0075
trend	-0.0345	0.0011	-0.0343	0.0011
constant	-8.1810	0.0665	-8.2036	0.0665
Nonlinear parameters:				
γ^a	-0.0263	0.0084	-0.0563	0.0083
γ^{ad}	0.0323	0.0077	0.0284	0.0160
γ^h	-0.0242	0.0094	-0.0369	0.0121
γ^{ICE}	-0.0448	0.0021	-0.0458	0.0020
Statistics:				
mean price elasticity	-1.8342		-1.9876	
Share of BEV owners charging:				
at home	0.6763		0.7286	
publicly	0.3237		0.2713	
Average kilometers driven by BEV owners charging:				
at home	22.4768		19.1484	
publicly	13.2549		8.8585	

Note: Volume is in cubic meters, weight in metric tons, horsepowers in kW and price in 1000 Euros. The charging station density is the logarithm of the number of charging stations plus one.

charging at stations using the demand results relying on moments G^1 and G^2. The charging pattern closely matches the observed patterns in Figure 3 as we match this curve exactly in G^2. The primary and slight difference in the shape of the charging pattern at stations is in the early morning and is due to our assumption that there is no charging at stations between 11 pm and 6 am. The charging pattern is flat due to our assumption that drivers randomly charge at stations whenever they are not driving.

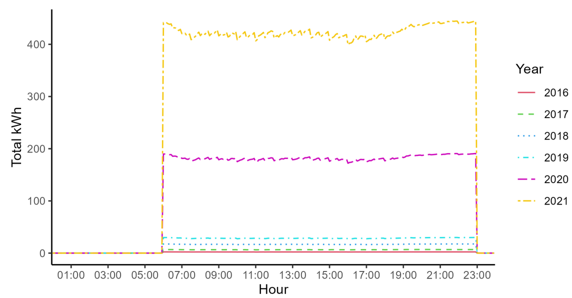
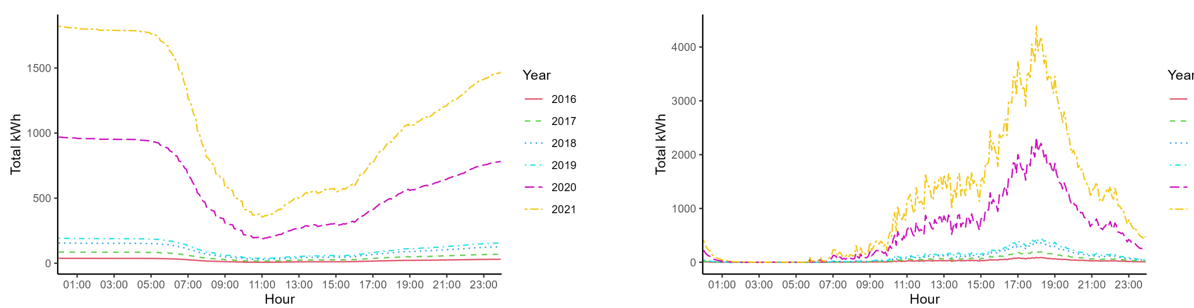


Figure 6: Mean daily model implied public charging

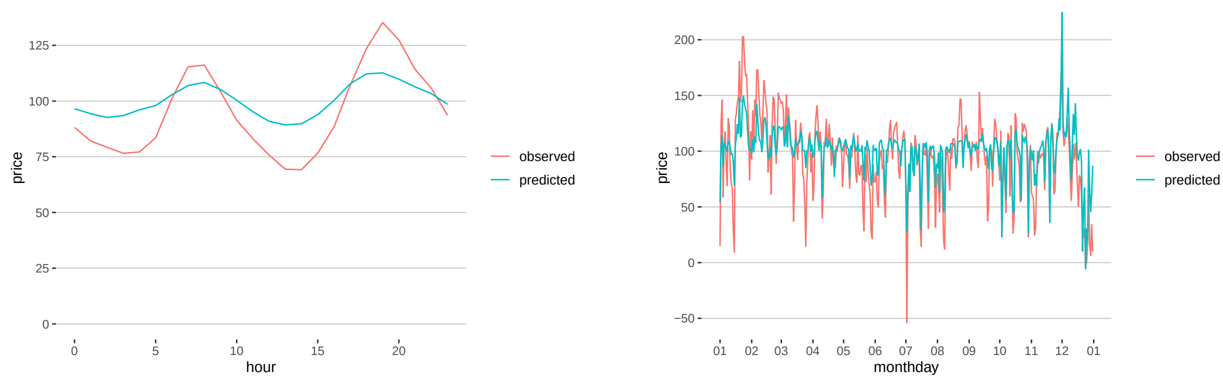
Figure 7: Mean daily model implied home charging



Uniform home charging | Home charging upon arrival

Figure 7 plots the model-implied charging patterns for home charging. The left panel plots charging when we randomly distribute charging over the period at home. The right panel plots the pattern when drivers plug in and start charging upon arrival at home. The left panel shows a load profile that starts increasing in the afternoon, is high throughout the night, and plunges around 7 am when drivers leave for work. The right panel concentrates the charging to earlier hours, so there is a strong peak between 5 pm and 7 pm. At night, there is almost no charging. This follows from two underlying reasons. First, 27% of EV buyers cannot home charge and consequently charge during the day at chargers. Second, our model predicts that EV home chargers drive, on average, 19km per day and thus only

Figure 8: Comparison of observed and predicted wholesale prices



Intra-day prices | Average daily prices

need a few hours every night to recharge their batteries. As we discuss next, the intraday charging pattern will matter for the electricity market equilibrium.

5.3 Electricity Market Simulations

We benchmark our model against the observed day-ahead wholesale prices we observe in 2023. The observed yearly average spot price in 2023 was EUR 95.18, whereas we predict a yearly average spot price of EUR 107.50. The correlation between the predicted and actual hourly spot prices is 0.72. Our model performs well at predicting actual outcomes, given its simplicity. Andrés-Cerezo and Fabra (2023) study the Spanish electricity market and find a correlation coefficient of 0.87.[18] Figure 8 plots the average intra-day spot prices (actual and predicted by our model). We predict a flatter load curve compared to reality, something that is well-known when assuming perfect competition and ignoring ramp-up costs (see Andrés-Cerezo and Fabra, 2023). Figure 8 plots the average daily spot prices throughout the year. Our model predicts a flatter price curve with less variance than observed. It generally tracks price movements well beyond extremely negative price events. These events occur because feed-in subsidies incentivize units to supply electricity even at a strongly negative price. In addition, some thermal units may find it profitable to supply electricity at negative prices to avoid costly ramping-down and ramp-up.

[18] Andrés-Cerezo and Fabra (2023) simulate the Spanish market for 2019 when hours with negative prices were less prevalent, and energy markets were less volatile.

6 Counterfactuals

In this section, we compute the joint equilibrium outcome, taking into account that electricity price increases lower consumers' willingness to purchase an EV. We simulate a counterfactual with current flat electricity rates and one with time-varying electricity rates.

We study the effects of a 10% EV stock on the electricity market. An EV stock of 10% translates into 4.8 million EVs on the road. We obtain this stock by multiplying the 2021 vehicle market equilibrium quantities (the flow) by a fixed factor of 27.95.[19] In the counterfactuals the flow changes as it is a function of electricity prices, but we multiply the flow with the same fixed factor to retain the interpretation of an EV stock share around 10%.

We compute equilibria under three electricity market scenarios:

1. Baseline: This scenario takes the observed load, renewable generation, and merit order from 2023.

2. 10% increase in renewables: This scenario increases renewable generation by 10%. This is roughly on par with the German government's annual renewable expansion goals, which aim to add roughly 10% of solar and wind generation capacity each year for the foreseeable future.

3. 10% increase in load: This scenario increases the hourly load by 10%, possibly due to electrifying other sectors or increased electricity usage by data centers. This scenario mimics a setting where there would be no entry of a new generation despite the increased demand.

Together, these three scenarios allow us to study how sensitive our results are to changes in the generating capacity. Overall, we expect that an increase in electricity demand should induce the entry of generation capacity when revenues increase. Still, entry into the electricity market is highly regulated and depends on available network capacity. We do not model endogenous entry and network capacity expansion.

For each counterfactual, we start from the 2021 vehicle market equilibrium and multiply the EV quantity of that market with the fixed factor. Next, we compute implied EV load curves and compute a new electricity market equilibrium. This results in a first set of results

[19] We have 171,735 EV sales in our sample for 2021. We scale that number up to get a 10% EV stock. There were roughly 48 million vehicles registered in Germany in 2021, so we scale up the 2021 EV sales by a factor of $\frac{10\% \times 48{,}000{,}000}{171{,}735} = 27.95$. By the end of 2021, there were 618,460 EVs on the road in Germany; by the end of 2023, that number had increased to 1.4 million. The German government aims to have 15 million EVs on the road by 2030.

that does not take into account the feedback loop between vehicle and electricity market. Next, we reiterate the procedure and update vehicle market and electricity market equilibria until we reach convergence and the equilibrium conditions in (3.5) are satisfied.

One outcome of interest that warrants some explanation is the increase in electricity expenditures, which we break up into charging expenditures and a pecuniary externality. In particular, we define the electricity expenditure as $E^B * p^w_{t,post} - E^B * p^w_{t,pre}$. This is the expenditure accruing to non-EV users. We can decompose the total change in expenditure as

$$\underbrace{E^D_{t,post} * p_{t,post} - E^D_{t,pre} * p_{t,pre}}_{\text{Change in electricity costs}}$$

$$=(E^B * (p^w_{t,post} + \mu) + E^{EV,h}_{t,post} * p^h_{t,post} + E^{EV,a}_{t,post} * p^a_{t,post}) - E^B_{t,pre} * (p^w_{t,pre} + \mu)$$

$$= \underbrace{E^{EV,h}_{t,post} * p^h_{t,post} + E^{EV,a}_{t,post} * p^a_{t,post}}_{\text{Charging expenditure}} + \underbrace{E^B * (p^w_{t,post} - p^w_{t,pre})}_{\text{Pecuniary externality}}$$

6.1 Quantifying the equilibrium feedback between vehicle and electricity markets

In this first analysis, we study the joint equilibrium with where retail and charging electricity rates remain fixed intraday, as is currently the case in Germany. Because the price schedule remains fixed over the charging period S, we do not need to recompute the solution for the charging model. The timing of charging stays constant in this counterfactual. It suffices to update the electricity expense terms that enter demand. These changes in expenses affect market shares and implied load curves, and we loop through these changes until we reach a fixed point. While the timing of charging changes, the equilibrium quantities of EV's and EV electricity load change in the counterfactual.

Table 5 shows the impact of a 10% EV stock on the vehicle and electricity markets. Column 3 (Baseline, No. eq. adjust.) shows the results from only adjusting the electricity market equilibrium in response to a 10% EV stock (akin to only carrying out the first step of the iterative procedure to find a new equilibrium). Columns 4-6 show the full equilibrium adjustment under the three scenarios described above. There are three main takeaways from this table.

First, EV charging generates a substantial pecuniary externality on electricity consumers (EV and non-EV users). Every Euro spent on charging creates a pecuniary externality of 66 cents. These costs of electrifying vehicles are paid by all electricity users, whether they own

Table 5: Counterfactual with 10% EV stock, assumes front-loaded charging

		Baseline		↑ 10% RES	↑ 10% load
Variable	No EVs	No eq. adjust.	Eq. adjust.	Eq. adjust.	Eq. adjust.
Generation (TWh)	459.605	+ 3.883	+ 3.859	+ 3.999	+ 49.557
Weighted price (EUR/mWh)	107.409	+ 1.570	+ 1.563	-6.947	+ 18.866
EV sales			-16,379	+79,825	-202,107
Charging expenditure (bil EUR)		1.095	1.095	1.099	1.085
Pecuniary externality (bil EUR)		0.722	0.718	0.656	0.841
Pecuniary externality per EUR spent		0.659	0.656	0.597	0.775

Note:
10% EV stock amounts to 4.8 million EVs in total.

an EV or not, and increase revenues for electricity retailers. While EV charging increases the electricity price by only 1%, the quantity of electricity consumed before electricity is very large. This explains the size of the pecuniary externality: prices increase a bit, but for a large consumption base.

Second, we find outcomes barely change between using the initial counterfactual step and considering the full joint equilibrium (column 3 vs column 4). In other words, changes in (weighted average) wholesale electricity prices do not have a large effect on EV uptake. The reason is that the electricity price increase of 1% is too small to change the EV uptake, which is determined by differences in fuel prices and electricity prices. This result, combined with the first result, showcases that the EV stock can generate substantial pecuniary externalities but that the electricity price increase will not put a backstop on EV adoption. With the current price schedule, the EV transition will not be stopped by electricity price increases, but it will cause a substantial increase in German electricity spending.

Third, we find that changes in electricity demand and supply interact with vehicle electrification surprisingly. First, expanding the electricity supply with 10% more renewables does not cause substantial reductions in the pecuniary externality. It remains 60 cents per Euro spent on charging. While the new capacity decreases average prices, the timing of EV charging is not aligned with the low prices generated by renewables, and thereby, EV charging keeps increasing electricity spending for everyone. Reversely, adding 10% more load increases the pecuniary externality to 78 cents per Euro spent on charging. EVs now require more costly thermal units to come online and meet demand. the peaks in the electricity load schedule are even more pronounced.

Table 6 presents the carbon pollution implications of a 10% EV stock.[20] We find the

[20]We focus on CO_2 emissions and ignore reductions in local pollutants. Adding local pollutants would require modeling air pollution as in Holland et al. (2021)

Table 6: Environmental implications from a 10% EV stock

		Baseline		↑ 10% RES
Variable	No EVs	No eq. adjust.	Eq. adjust.	Eq. adjust.
Emissions (mio t)	157.668	+ 2.623	+ 2.607	-14.250
EVs: gCO2/km		91.881	91.329	88.422
Allowance cost (bil EUR)	13.339	+ 0.222	+ 0.221	-1.206

Note:
Assumes carbon price of EUR 86.5/tCO2

emissions intensity of EVs to be 91gCO2/km. Notice that this number contains the actual marginal emission of the EV stock obtained by integrating each change in pollution caused at each hour of the market. As a comparison, the current EU fleet emissions target is 95gCO2/km.[21] EVs actual emissions would thus barely help with reaching the 95gCO2/km target for firms if the EU would assign actual CO2/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.

Increasing renewable generation by 10% (Germany's yearly goal) decreases the emissions intensity of EVs by only 3gCO2/km, suggesting that greening the electricity grid plays some role in making EVs greener, but the time at which EVs charge under flat electricity rates makes them polluting because without exposure to wholesale electricity prices, EVs often charge when the marginal supplier of energy is dirty.

6.2 Time-varying electricity rates: a triple dividend

The previous subsection shows that EV charging imposes a substantial pecuniary externality on electricity users and that EVs cause a substantial amount of pollution, despite being counted as zero-emission vehicles in the EU regulation. In this section, we analyze the role that real-time prices for home charging can play in reducing the pecuniary externality and environmental damages of EVs.

While real-time pricing tariffs for EV users are not yet available in Germany, it is a clear goal to make it easier for companies to offer these tariffs to consumers. Upon the passing of a bill making it easier to roll out smart meters, the Germany's Federal Minister for Economic Affairs and Climate Action, Robert Habeck, stated that "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

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

an intelligent way.".[22]

Table 7: 10% EV share, front-loaded vs uniform charging

	Front-loaded home charging			**Uniform home charging**		
Variable	Total	Home	Public	Total	Home	Public
Generation (TWh)	+ 3.883	+ 3.001	+ 0.882	+ 3.883	+ 3.001	+ 0.882
Weighted price (EUR/mWh)	+ 1.570	+ 1.227	+ 0.350	+ 0.972	+ 0.642	+ 0.367
Charging expenditure (bil EUR)	1.095	0.698	0.397	1.095	0.698	0.397
Pecuniary externality (bil EUR)	0.722	0.564	0.161	0.447	0.295	0.169
Pecuniary externality per EUR spent	0.659	0.808	0.406	0.408	0.423	0.426
Emissions (mio t)	+ 2.623	+ 2.028	+ 0.598	+ 2.640	+ 2.044	+ 0.597
EVs: gCO2/km	91.881	92.013	91.078	92.258	92.763	91.021
Allowance cost (bil EUR)	+ 0.222	+ 0.172	+ 0.051	+ 0.223	+ 0.173	+ 0.051

Note:
10% EV stock amounts to 4.8 million EVs in total.

Table 7 breaks down the impact of a 10% EV stock into home and public charging and shows results under the different assumptions of how consumers home charge: distributed uniformly across the night or charge upon arrival at home. Two results are worth highlighting. First, home charging is responsible for the brunt of the additional load, expenses, and emissions. This is because 70% of EV adopters home charge and because they have higher mileages than away chargers. Moreover, home charging creates double the pecuniary externality of public charging (81 cents per Euro spent vs 41 cents per Euro spent). Public charging happens more throughout the day and less in the evening when the peak in pricing is most pronounced. However, public charging is only marginally less emission intense than home charging; often, the marginal supplier is a polluting source, also during the day.

Second, the pecuniary externality reduces substantially from 80 cents to 41 cents per Euro charged if we assume consumers spread their home charging uniformly over the time at home. Now, the pecuniary externality is even slightly lower than the public charging pecuniary externality (42 cents per Euro spent), showcasing the importance of avoiding charges during peak times.

Overall, Table 7 suggests substantial gains from shifting charging behind peak hours exist. In the next section, we analyze the effects of incentivizing EV users to do so by exposing them to time-varying wholesale prices.

To study the effect of real-time pricing for home charging, we solve the system described in 3.5 with time-varying prices. We assume that the overall retail prices remain time-invariant

[22]https://www.bmwk.de/Redaktion/EN/Pressemitteilungen/2023/01/20230111-the-cabinet-adopts-relaunch-of-the-digitisation-of-the-energy-transition-and-paves-the-way-for-accelerated-smart-meter-rollout.html

Table 8: Counterfactual with 10% EV stock and real-time pricing for home charging

		Observed demand/supply
Variable	No EVs	10% EV stock
Generation (TWh)	459.711	+ 4.017
Weighted price (EUR/mWh)	107.441	+ 0.160
EV sales		+158,774
Charging expenditure (bil EUR)		1.095
Pecuniary externality (bil EUR)		0.073
Exp. ext. per EUR spent		.067

Note:
10% EV stock amounts to 4.8 million EVs in total.

but that EVs face specific contracts exposing them to hourly wholesale generation costs plus a fixed markup. We calculate this markup so that initial prices remain the same on average in the initial market, and we start from a time-varying and fixed pricing schedule with the same average prices.

To construct the time-varying price schedule, we set the hourly price equal to the average wholesale price that would have prevailed at that hour without EV charging in 2023, according to our estimation. The equilibrium simulation is computationally much more demanding as it requires a new solution for the 11 million charging cost minimizations each time there is a change in the order of the electricity rate sequence over the day.

Tables 8 and 9 show the effects of exposing consumers to real-time pricing without accounting for the full feedback loop. In other words, these tables show how real-time pricing affects optimal charging and vehicle purchase decisions and how the resulting intra-day load curve from charging affects the electricity market, without accounting for the full feedback loop between the electricity market and the vehicle market.[23]

Table 8 suggests that exposing home chargers to real-time pricing generates a striking triple dividend. First, the pecuniary externality is almost completely eliminated to only around 7 cents per Euro spent on charging. Second, because real-time pricing enables EV users to charge at prices substantially below the fixed price, operating costs decrease, and EV sales increase by 3% accordingly. This benefit of real-time pricing is revealed thanks to the explicit computation of the complementary equilibrium of electricity and vehicle markets. The third part of the triple dividend is visible in Table 9. Per-km CO2 emissions of EVs

[23] We face an additional computational problem due to the appearance of shadow peaks. All consumers face the same deterministic price schedule and charge at the same moment generating sharp peaks rather than smooth demand. We need to introduce noise across individuals to avoid this problem. Bailey et al. (2024) find these shadow peaks are an actual concern in an experimental setting, showing that practical implementation of time-varying prices will likely have to be designed in tandem with local temporary rationing.

drop by 28% to around 65 gCO2/km. EVs are now clearly very green cars and way greener than a smaller combustion engine.

Table 9: Environmental implications under real-time pricing

Variable	No EVs	No eq. adjustment
Emissions (mio t)	157.740	+ 1.953
Allowance cost (bil EUR)	13.345	+ 0.165
EVs: gCO2/km		65.530

Note:
Assumes carbon price of EUR 86.5/tCO2

The reason for why this triple dividend occurs can be seen in Figure 9. Real-time pricing shifts the EV load away from the peak hours, decreasing upward price pressure and pushing EV charging into hours in which the real-time price is substantially below the fixed price (red line). Cheaper EV charging pushes up EV sales. Electricity generation in the hours during which EVs now charge is also less emissions-intense. The CO2 price that is imposed on electricity generators ensures that wholesale prices correlate strongly with emissions generated, which makes EV charging greener.

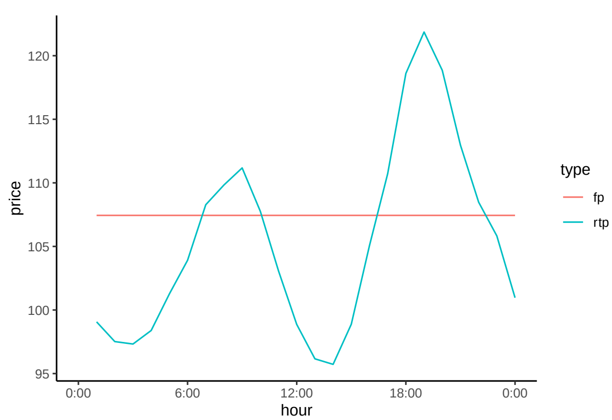


Figure 9: Real-time vs flat prices

7 Conclusion

We build and estimate a joint equilibrium model of the new passenger vehicle and electricity markets in Germany, modeling EV owners' optimal charging decisions, vehicle choices, and wholesale prices. The model allows us to study the impact of vehicle electrification on electricity markets, as well as the full feedback loop between EV demand and electricity prices.

We have four main findings. First, under the current electricity pricing structure, we find that EVs cause a substantial pecuniary externality: every €1 spent on charging increases electricity expenditures by €0.66 for all electricity consumers. Second, we find that EV demand hardly decreases in response to the (mild) electricity price increases it creates. Rising electricity prices do not limit EV adoption until the EV stock expands far beyond 10%. Third, in the current German electricity market, EVs are not much greener than the EU standard for combustion engines.

Fourth, exposing EV home chargers to wholesale price variation generates a triple dividend. It reduces the pecuniary externality by 90%. Since EV owners now internalize the effects of their decisions on wholesale prices, they shift charging to hours in which wholesale prices are lower and do not cause further price increases at peak. Time-varying prices for home chargers decrease EV emissions by 30%. The carbon price imposed on electricity generation through the EU Cap-and-Trade scheme aligns private and social marginal costs so that hours with low wholesale prices tend to be hours with low emissions from electricity generation. Finally, time-varying pricing for home chargers increases EV sales by 3%. Since EV users now charge when electricity prices are lower than the flat tariff, EV operating costs go down substantially, and consequently, EV sales go up.

Our findings highlight substantial benefits to making EV charging flexible and exposed to wholesale electricity costs. Indeed, exposing EV owners to time-varying prices for home charging creates a triple dividend, leaving the environment, other electricity users, and EV owners themselves better off.

Our findings suggest that installing more renewable capacity helps make EVs greener, but not as much as time-varying prices. Increasing renewable output by 10% decreases per-km CO2 emissions by around 3%. We also expect the pecuniary externality to shrink when generating capacity enters in response to increased rents. Vehicle electrification policies can have a crucial impact on the entry incentives of electricity generators. Our model provides a first building block to understanding how EV policies affect these long-run and hard-to-reverse entry decisions, crucial for the cost and environmental implications of large-scale vehicle electrification.

References

Alé-Chilet, J., Chen, C., Li, J., and Reynaert, M. (2021). *Colluding against environmental regulation.* Centre for Economic Policy Research.

Allcott, H. and Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. *The Review of Economics and Statistics*, 96(5):779–795.

Andrés-Cerezo, D. and Fabra, N. (2023). Storage and renewable energies: Friends or foes. Technical report, Working Paper.

Armitage, S. and Pinter, F. (2021). Regulatory Mandates and Electric Vehicle Product Variety. *Working Paper*.

Bailey, M., Brown, D., Shaffer, B., and Wolak, F. (2025). Show me the money! a field experiment on electric vehicle charge timing. *American Economic Journal: Economic Policy*.

Bailey, M., Brown, D. P., Myers, E., Shaffer, B., and Wolak, F. A. (2024). Electric Vehicles and the Energy Transition: Unintended Consequences of a Common Retail Rate Design. *Working Paper*.

Benetton, M., Compiani, G., and Morse, A. (2023). When cryptomining comes to town: High electricity-use spillovers to the local economy. Technical report, National Bureau of Economic Research.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Burlig, F., Bushnell, J., Rapson, D., and Wolfram, C. (2021). Low energy: Estimating electric vehicle electricity use. In *AEA Papers and Proceedings*, volume 111, pages 430–35.

Bushnell, J. B., Muehlegger, E., and Rapson, D. S. (2022). Energy prices and electric vehicle adoption. NBER Working Papers 29842.

Busse, M. R., Knittel, C. R., and Zettelmeyer, F. (2013). Are consumers myopic? evidence from new and used car purchases. *American Economic Review*, 103(1):220–56.

Butters, R. A., Dorsey, J., and Gowrisankaran, G. (2021). Soaking up the sun: Battery investment, renewable energy, and market equilibrium. NBER Working Papers 29133.

Chatterjee, C., Fan, Y., and Mohapatra, D. P. (2022). Spillover effects in complementary markets: A study of the indian cellphone and wireless service markets. Technical report, Technical report, Working Paper.

Dorsey, J., Langer, A., and McRae, S. (2022). Fueling alternatives: Gas station choice and the implications for electric charging. NBER Working Papers 29831.

EWI (2024). Dokumentation ewi merit order tool 2023.

Fournel, J.-F. (2021). Electric Cars and Network Effects: Are Subsidies the Right Tool for Reducing Emissions? *Working Paper*.

Gandal, N., Kende, M., and Rob, R. (2000). The dynamics of technological adoption in hardware/software systems: the case of compact disc players. *The Rand Journal of Economics*, pages 43–61.

Gandhi, A. and Houde, J.-F. (2019). Measuring Substitution Patterns in Differentiated Products Industries. NBER Working Papers 26375.

Gillingham, K., Ovaere, M., and Weber, S. M. (2024). Carbon policy and the emissions implications of electric vehicles. *Journal of the Association of Environmental and Resource Economists*.

Grieco, P. L., Murry, C., and Yurukoglu, A. (2024). The evolution of market power in the us automobile industry. *The Quarterly Journal of Economics*, 139(2):1201–1253.

Grigolon, L., Park, E., and Remmy, K. (2024). Fueling electrification: The impact of gas prices on hybrid car usage. *ZEW-Centre for European Economic Research Discussion Paper*, (24-017).

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 10(1):33–54.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016). Are there environmental benefits from driving electric vehicles? the importance of local factors. *American Economic Review*, 106(12):3700–3729.

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

Holland, S. P., Mansur, E. T., and Yates, A. J. (2022). Decarbonization and Electrification in the Long Run. NBER Working Papers 30082, National Bureau of Economic Research.

International Energy Agency (2024). Global ev outlook 2024. Technical report.

Jia Barwick, P., Kwon, H.-S., and Li, S. (2022a). Attribute-based subsidies and market power: An application to electric vehicles. *Working Paper*.

Jia Barwick, P., Li, S., Waxman, A., Wu, J., and Xia, T. (2022b). Efficiency and equity impacts of urban transportation policies with equilibrium sorting. *Working Paper*.

Joskow, P. L. and Wolfram, C. D. (2012). Dynamic pricing of electricity. *American Economic Review*, 102(3):381–85.

Jullien, B. and Bouvard, M. (2022). Fair cost sharing: big tech vs telcos.

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

Lesellier, M., Boucher, H., and Gökkoca, G. (2023). Testing and relaxing distributional assumptions on random coefficients in demand models. Technical report, Toulouse School of Economics.

Li, J. (2019). Compatibility and investment in the us electric vehicle market. *Working Paper*.

Li, S., Tong, L., Xing, J., and Zhou, Y. (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.

Miravete, E. J., Moral, M. J., and Thurk, J. (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, E. and Rapson, D. S. (2022). Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California. *Journal of Public Economics*, 216.

Remmy, K. (2023). Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles. *Working paper*.

Reynaert, M. (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.

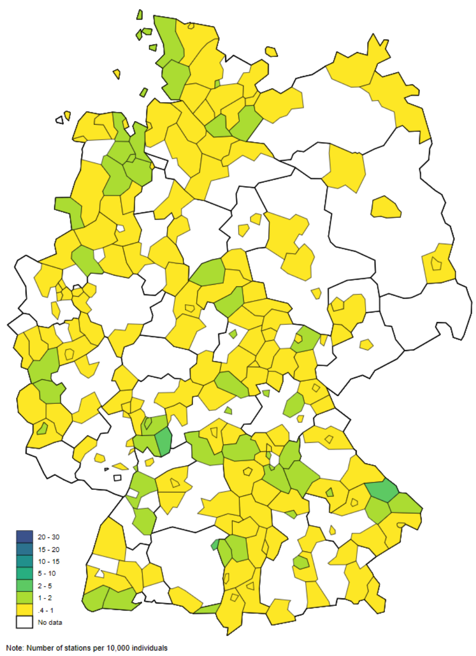
Sinyashin, A. (2021). Optimal Policies for Differentiated Green Products: Characteristics and Usage of Electric Vehicles. *Working Paper*.

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

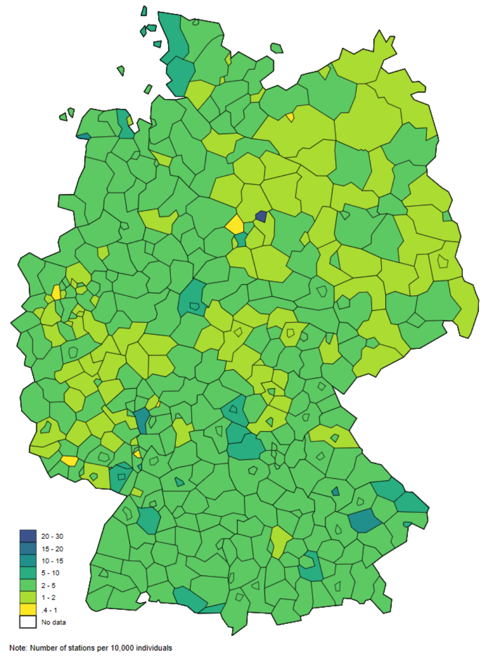
Xing, J., Leard, B., and Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management*, 107:102432.

A Appendix

A.1 Additional Figures and Tables



2017



2021

Figure A1: Public chargers per 10k inhabitants by county

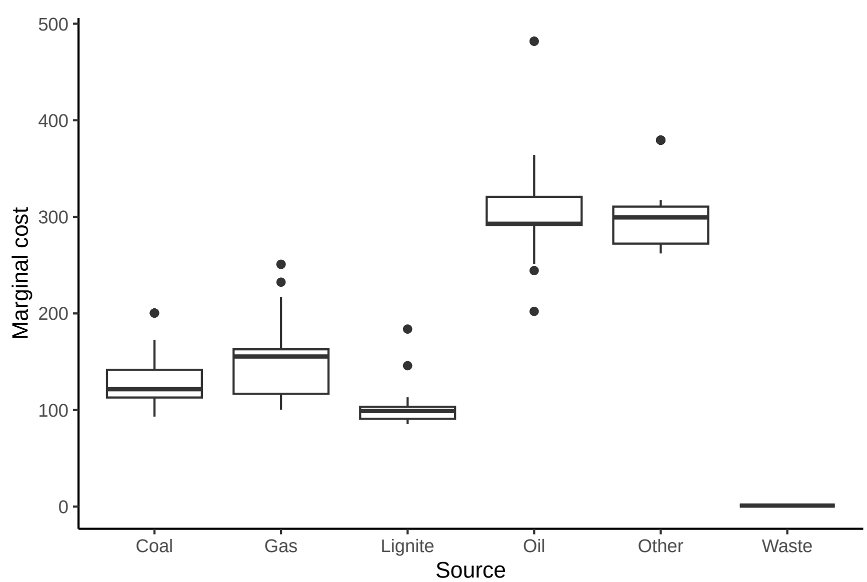


Figure A2: Marginal costs by generation type (in € /MWh)

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

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

Note: We assume a carbon price of EUR 83.66 per t/CO2.

A.2 Adjustment of public charging demand

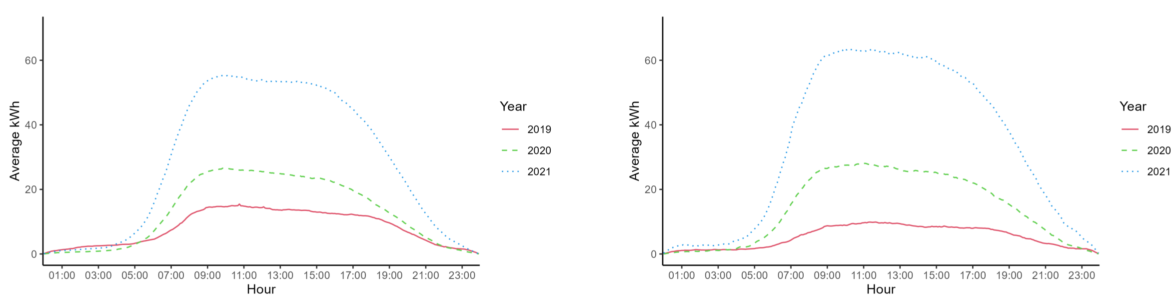
Only for the state Hamburg we observe charging at most charging stations. For all states (including Hamburg) we have data on charging at only subsidized charging stations. In Table A2 we see that only about 25 to 30 percent of charging points in Germany are subsidized. As our demand and charging model predict charging at all charging points per state, we need to scale up observed charging from subsidized to all charging points.

Year	**Subsidized**	**Total**
2019	7654	27016
2020	11188	37993
2021	14945	52466

Table A2: Number of charging points by year

In Figure A3 we show that there is a selection concern saying that subsidized and unsubsidized do not see the same demand. On the left we take the observed data of most charging points in Hamburg. On the right we scale up the observed charging at subsidized charging points to match the same number of charging points as on the left. We check counterfactually on the right what would happen if unsubsidized charging points had the same demand as subsidizied charging points.

Figure A3: Observed and scaled up public charging in Hamburg



Observed public charging

Scaled charging from subsidized stations

We can see that this assumption does not hold. Notably in 2021, there is counterfactually more charging than observed which indicates that subsidized charging points have seen more demand than unsubsidized. This also holds for 2020 but the reverse is true for 2019. The mean absolute deviation across all years and five minute intervals is around 32 percent.

From the two datasets in Hamburg we can derive the average demand per subsidized and unsubsidized charging point. We get the ratio of the two by year and assume that selection, i.e. this ratio, is the same in Hamburg as in all other states per year. Using this information we can scale up the observed charging at subsidized charging points to all charging points in each state accounting for selection into subsidies.

As in our demand model we only focus on private sales of BEVs and the observed charging is that of all BEVs we need to apply a second correction. We scale down the observed charging by the share of BEV stock of private persons in each state and year.