When Will Electric Vehicles Connect to the Grid?

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Abstract

The transition to predominantly electricity-powered personal vehicles poses major challenges to policymakers. A crucial aspect is the timing of intraday charging of electric vehicles (EV). The electricity market equilibrium depends on the intraday distribution of the additional load from EVs. This affects the amount of pollution from energy supply: renewables are the marginal generation source at some but not all points of the day. We build and estimate an equilibrium model for Germany where we model EV owners' optimal charging decision, car demand, charging station entry, and the electricity market. We rely on rich individual-level data on daily driving patterns and data from charging station demand to investigate when EVs are charged intraday within the current policy framework. Our empirical model allows us to study how policy options such as demand subsidies, charging station subsidies, and electricity rates affect the interplay between EV demand, the electricity market, and resulting pollution levels.

1 Introduction

Electric vehicles have seen a dramatic revival in the past 10 years. Governments worldwide subsidize EV adoption and the entry of charging stations that are needed to offer users the ability to replenish their batteries. The ultimate goal is that widespread EV adoption will decarbonize public road transport, which is crucial to keeping global temperatures from rising to catastrophic levels.

Decarbonization via electrification of the car fleet needs to overcome two challenges: First, the electricity that EVs charge needs to be carbon-free. As long as the electricity generation mix contains thermal generation units, the environmental benefits of EVs depend crucially on the time of day they connect to the grid. Second, EV usage costs must be competitive with conventional cars. To achieve competitiveness, users need to satisfy their driving needs with the available EV range and charging network. In turn, these technical factors also influence when people charge their cars.

In this paper, we study when electric vehicles connect to the grid and what this means for CO2 emissions and the costs of electrifying the vehicle fleet. We do so by building and estimating a model of EV adoption, individual car usage, charging station entry, and electricity demand. We rely on rich individual car usage data to analyze when EVs connect to the grid under the current policy framework. Our framework also allows for detailed substitution patterns that micro-found the role of EV range and charging station networks in EV adoption. Our model allows us to consider a rich set of policy counterfactuals to analyze how policies affect intraday electricity demand.

We build a charging model that maps the exogenous individual driving patterns into the amount and timing of battery charging for using an EV. We model this as a finite horizon dynamic discrete choice problem as individuals plan their charging to meet their planned driving for a limited time horizon. The model is related to the charging model for commercial battery operators by Butters et al. (2021). As our setting of private EV owners is different, though, our model differs in several important aspects. The battery owners in their model are all the same, while our problem differs depending on an EV owner's exogenous driving demand, home status, and home charging availability. Further, we do not allow EV owners to resell their charged energy. Rather, their only means of depleting the battery is by driving. From solving this model, we derive the optimal cost of electricity from home and public charging for a given EV in a given market and per individual. This model enables us to study the timing of electricity load from EVs intraday, and we can use the derived expected electricity costs as attributes in a car demand model.

In the car demand model, we follow Berry et al. (1995), using aggregate car registration data. Heterogeneous consumers choose between differentiated cars. We extend the standard model by plugging in the expected electricity cost from charging an EV which we micro-found with our charging model. This is similar to the modeling in Jia Barwick et al. (2022) who plug in the solution of a transportation mode choice model into a model of location

choice for housing. We further consider network effects between the public charging station density and the demand for EVs. Price and charging station density pose challenges for the identification of the demand model which we remedy with the choice of appropriate instruments.

Lastly, we model public charging station entry. We extend previous approaches in Springel (2021) and Remmy (2023) by accounting for the fact that realized public charging demand is decisive for charging station entry and not simply the cumulative EV base. Having this model at hand allows us to predict how charging station density changes with subsidies for potential entrants. It further captures feedback effects from increased charging station density when policymakers use other instruments such as demand subsidies or real-time electricity pricing.

We plan to consider three counterfactuals. In the first counterfactual, we evaluate the effects of purchase subsidies. Such a subsidy makes EVs cheaper for all driver types. Unlike previous studies, feedback loops from indirect network effects will depend on the additional local demand for public charging induced by the purchase subsidy. These network effects will be small in areas where people mainly charge at home. However, these areas are also likely to be the ones where purchase subsidies are most effective. When home charging is available, the main obstacle to EV adoption is likely the price difference between conventional and electric cars, which the purchase subsidy reduces. Hence, such a purchase subsidy will likely increase electricity demand at night.

We evaluate the effects of subsidizing public charging station entry in the second counterfactual. The resulting increase in public chargers will have a differential effect on EV users. Users that cannot home charge will see their disutility from buying an EV go down, whereas users with the ability to home charge will not see their utility from buying an EV affected. Thus, such a subsidy likely leads to additional EV uptake in urban areas where many users rely on public charging and increase demand for electricity during the day.

We plan to evaluate the effects of introducing time-varying electricity prices in the third counterfactual. Such a pricing scheme would incentivize users to charge outside of peak hours. Day-time charging would likely become more expensive, shifting electricity demand from EVs behind the evening peak into the night. While easing the strain on the grid and reducing peak prices, such a scheme may lead to the bulk of charging occurring after the sun has gone down and solar PV generation has retired for the day. Such a scenario could uncover interesting interactions between electricity demand and renewable-induced supply shifts.

Related literature

We contribute to a young and fast-growing literature studying the EV transition. This literature has focused on different aspects of the EV transition. Li et al. (2017), Li (2019),

Springel (2021), and Fournel (2021) study the role of indirect network effects in EV adoption. These papers measure indirect network effects by making EV adoption a function of the size of the charging network and charging station entry a function of the total number of EVs circulating. Li (2019) refines this approach to study the compatibility between different types of EVs and charging points. Xing et al. (2021) and Muehlegger and Rapson (2022) study the role of purchase subsidies with a focus on the type of car a subsidized EV replaces. Armitage and Pinter (2021), Jia Barwick et al. (2022) and Remmy (2023) study supply-side effects of EV subsidy schemes. Armitage and Pinter (2021) focus on incentives to enter new vehicles while Jia Barwick et al. (2022) and Remmy (2023) focus on strategic price and product attribute responses of EV makers to subsidies. Sinyashin (2021) and Bushnell et al. (2022) study the role of relative usage costs between electric and conventional cars in purchase decisions. Dorsey et al. (2022) study the hassle cost differences between home and away charging and the implications for public charging network design. Holland et al. (2016), Burlig et al. (2021), and Holland et al. (2022) study the relationship between EV adoption and the electricity sector. Holland et al. (2016) estimate the effects of widespread EV adoption on electricity demand by relying on ad-hoc assumptions on charging profiles.

We make three 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 in which we can evaluate how EV policies can shape load curves and 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.

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.

2 Data and Institutional Setting

We build a comprehensive data set of new car purchases, car usage, public charging station entry, and public charging station usage in Germany from 2005 to 2021. We combine several data sources.

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, which we treat as sales. A firm-and-trim identifier ("HSN/TSN") identifies a model. This identifier is defined at the car class-body type-engine type-horse power-weight-number of doors-level.

Car prices and characteristics. We complement the quantity data with scraped data on car prices and characteristics from the General German Automobile Club (ADAC). We can match both data sets using the HSN/TSN identifier, resulting in a data set containing quantities, prices, and car characteristics for 2005-2021.

EV charging stations. Data on public charging stations comes from the Federal Network Authority and contains a list of all public charging stations. The data set has information on the location, opening date, charging speed, and the number of charging points.

Public charging usage data. We have data on the usage of most public charging stations in Hamburg, which was provided by Stromnetz Hamburg. The data lists every charging event at a public charger from 2016 to 2021. It contains information on the length of the charging event, the amount of kWh charged, the start and end times of the event, and the location of the station.

Individual 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 at work in 5-minute increments for one day. If the individual was using the car we also observe the distance driven. We also have information on the type of dwelling the individual lives in (single-home vs two-family home vs apartment building), the income and other demographics, the state of residence, and the degree of urbanization of the user's county of residence.

2.1 User profiles

The individual usage data provides us with many different driver profiles. We employ k-means clustering to collect these individual profiles into five driver types.

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 1, 2, and 4 are users who drive in the morning and then again in the afternoon or early evening, likely to commute to and from work. Group 5 mainly drives around lunchtime, while Group 3 scatters their driving across the day. Looking at the black line, we see that almost all driving takes place 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

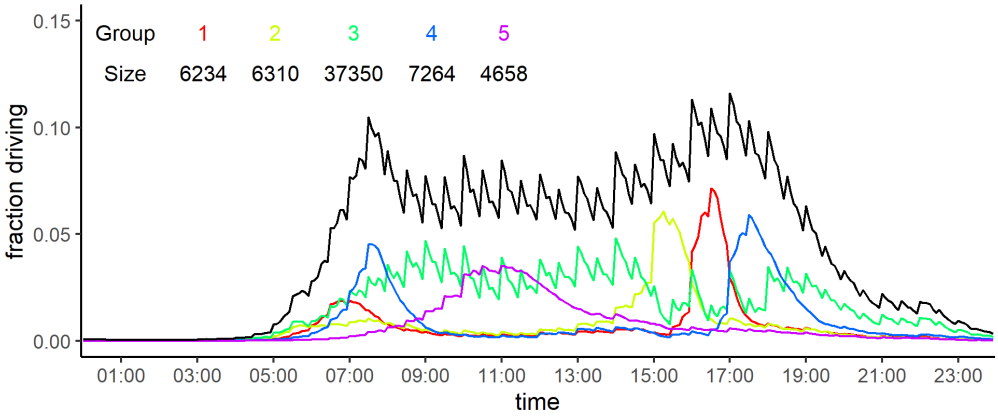


Figure 1. Probability density for different drivers on the road

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. Home charging availability by county type

	Metropolitan	Urban	Mainly Rural	Rural
Share of home charging availability	0.32	0.67	0.73	0.74

Table 1 shows the share of users who can home charge across different county types. We see that only a third of users living in metropolitan areas can home charge, whereas almost three-quarters of users in rural areas can home charge.

2.2 Public charging stations

Roll-out

Our data on public charging stations allow us to build a panel of the cumulative number of charging stations by county and by year. Due to the lackluster initial roll-out, the German government implemented a subsidy scheme to incentivize charging station entry that started in 2017. The scheme consisted of an 8,000 subsidy for the installation and grid connections of a charging station[1].

[1]This subsidy applied for charging stations with a charging speed up to 22kw, so-called Level-2 chargers. Larger subsidies existed for faster Level-3 chargers. However, the majority of chargers installed until 2021 were Level-2 chargers.

Figure 2. Public chargers per 10k inhabitants by county

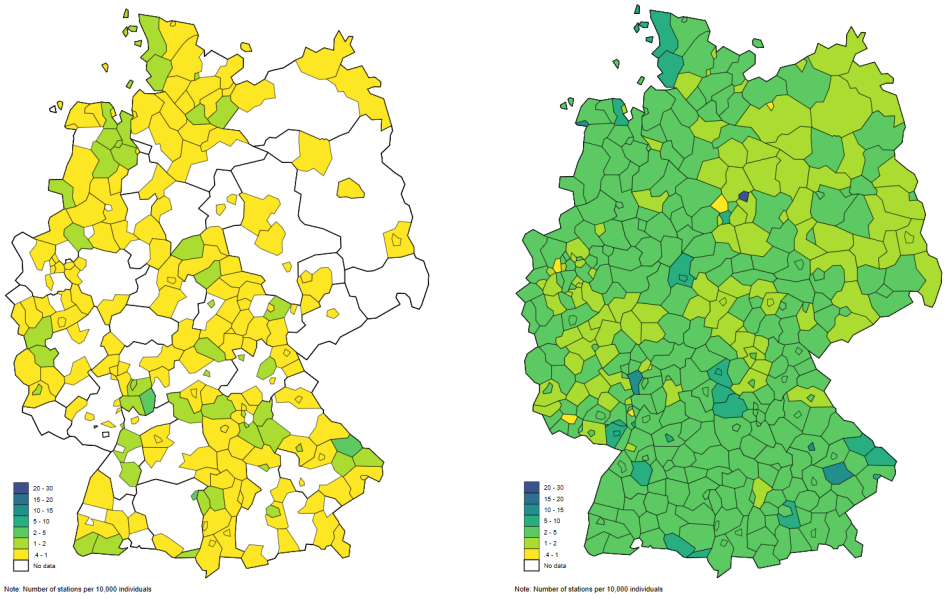


Figure 2 shows the number of charging points per capita by county in 2017 and 2021. Whereas many (mostly very rural) counties had zero charging points in 2017, every county had public charging points in 2021, with some having more than 20 public charging points per 10,000 inhabitants. The roll-out of public charging stations was also fairly uniform, with the bulk of counties having 2-5 public charging points per 10,000 inhabitants in 2021. Until the end of 2018, car makers did not install public charging points.[2] The largest providers of public chargers are electricity generators, supermarkets, local utilities, and start-ups specializing in providing chargers. Nationally, the market is fragmented. In 2021, the 10 largest firms operated around 26% of all public charging points. However, the market is more concentrated at more granular levels.

Usage

We obtained data on public charging point usage from StromNetz Hamburg, the largest provider of public charging points in Hamburg. We have information on usage at the charging point level from 2016-2021.

[2]Tesla operates its own network of public chargers. However, these chargers were only accessible to Tesla users during our sample period, so they do not qualify as public chargers.

Table 2. Evolution of charging point usage in Hamburg (104 million mWh market)

Variable	2016	2017	2018	2019	2020	2021
Market Total						
mWh charged /year	161	399	974	1,843	2,786	6,238
# charging points	205	495	684	832	866	1,009
EV Stock	858	956	1,387	2,233	3,395	7,035
Median charging point						
kWh charged /year	368	535	1,123	1,759	3,069	6,281
Charges /year	48	52	100	140	216	441
Hours Charged /day	0.27	0.37	0.84	1.22	1.94	3.70
Per EV						
Charging points	0.24	0.52	0.49	0.37	0.26	0.14
# charges /year	20	42	62	66	62	64
kWh charged /year	189	417	703	826	821	887

Table 2 gives an overview over the usage of public chargers in Hamburg. The total amount of electricity demanded at public chargers rose 38-fold from 2016 to 2021. At the same time, the number of chargers rose 5-fold and the number of EVs rose 8-fold. These numbers suggest that the occupancy of chargers has increased. This becomes evident in lines 4-6 of Table 2, which show that electricity demanded, the number of charging events, and the length of occupancy per charger all increased. In lines 7-9, we compare the evolution of station usage to the cumulative number of EVs registered in Hamburg. The number of charging points per EV registered in Hamburg has decreased over the sample period, while the per-EV usage has increased. These trends suggest that public chargers in Hamburg are not congested. In 2021, the average amount of electricity charged by EV registered in Hamburg was 887 kWh. Assuming the EV uses 15kWh/100km and an annual mileage of 13,000km these 887kWh charged represent around 41% of the required annual electricity.

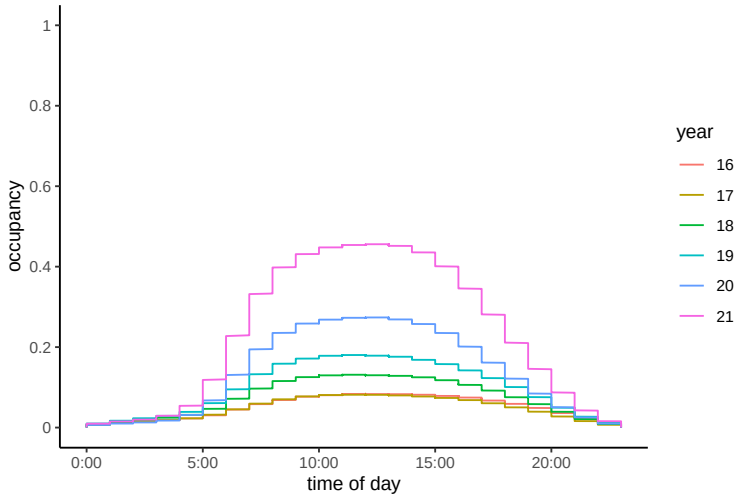


Figure 3. Mean occupancy of points

Figure 3 plots the average probability of a charging point being occupied at a given time of day across a year in 5-minute intervals. We see that occupancy increased from 2016-2021. Interestingly, occupancy is almost 50% from around 9 am to around 5 pm in 2021, but almost zero during the night.

3 Model

This section introduces a model of EV owners' individual charging behavior, car demand, and public charging station entry. The predictions of the charging model are plugged into the car demand model, which is related to the modeling in Jia Barwick et al. (2022). The charging model is a micro-founded model of optimal charging behavior. To our knowledge, we are the first to propose such a model. A related approach is taken by Butters et al. (2021) who model the charging behavior of commercial battery owners. While being similar their modeling differs in the sense that they do not look at private owners and the battery is charged and discharged for a price. In our setting car owners charge their car in order to meet their exogenous driving demand and obviously do not obtain a price for discharging their battery. Car owners therefore cannot freely choose any hour of the day to charge or discharge their battery. This is different from commercial battery owners who can choose freely and their charge and discharge behavior is purely driven by arbitrage motives. Lastly, we model the entry decisions of public charging stations. We extend the modeling in Springel (2021) and Remmy (2023). We make use of additional data on public charging demand in Hamburg. It allows us to estimate a demand model for public charging which potential entrants can use to predict the amount of public charging. This amount fundamentally depends on the number of EVs owned by individuals that predominantly charge their EV at public charging stations. We therefore take into account that effective public charging demand matters for entry of charging stations which renders our model

more realistic than previous attempts that incorporated network effects solely based on the total EV base.

In the charging model, an individual chooses over a two-week horizon in which 5-minute windows to charge their EV. They do so in order to meet their exogenous driving demand taking into account the additional constraints coming from the electricity consumption and battery size of the car as well as the speed of charging. Their objective is to minimize their monetary electricity cost minus a reward from consecutive charging. EV owners that can charge at home make the choice of whether they want to meet their electricity needs by home or public charging. We assume that potential car buyers project their minimal electricity cost for each EV and hence the outcome of this cost minimization problem enters their indirect utility from buying this car.

In the demand model, individuals choose to buy a car that maximizes their indirect utility which features heterogeneous preferences. The crucial ingredient here is the individual heterogeneity in the charging cost of EVs coming from the charging model. We further take into account that an expansion of the public charging station network affects an individual's disutility from public but not from home charging.

In our charging station entry model, we assume that symmetric charging stations decide each period to enter or not. This allows us to pin down the number of charging stations in each market as a function of realized public charging demand. We therefore take into account network effects between the public charging network and the number of EVs that are owned by individuals that predominantly charge away from home.

3.1 Charging Model

This model has two purposes. It serves as an ingredient for the demand model and hence applies to potential car buyers. However, it also helps to predict the timing and amount of electricity charged by EV owners. Individuals choose their intraday charging over a certain time horizon by minimizing their electricity cost minus some benefit from consecutive charging. The inconvenience of interrupted charging motivates the latter aspect. The minimization problem differs by individual due to her car usage patterns and dwelling type, of the EV through its range, and of the market the individual lives in through the market- and time-specific electricity rates.

We assume that an individual i is defined by her intraday car usage profile and home charging availability. The former consists of her home status $\mathbf{h}_i = (h_{is})_{s=1}^{S}$, her driving profile $\mathbf{r}_i = (r_{is})_{s=1}^{S}$ and her distance driven when using the car $\mathbf{m}_i = (m_{is})_{s=1}^{S}$. A period s consists of a five-minute interval and we take the time horizon S for our empirical application to be 14 days. The first two are binary vectors while the last one gives the number of kilometers driven within a period and hence is a vector of zeroes and integers above zero when driving, i.e. whenever $r_{is} = 1$. Lastly, home charging availability is captured by l_i which is zero if the individual cannot home charge and one otherwise. We

combine the individual heterogeneity into $\mathbf{w_i} \equiv (\mathbf{r_i}, \mathbf{h_i}, \mathbf{m_i}, l_i)$ for later reference.

The relevant features of a car j are the battery size R_j in kWh and the per kilometer electricity consumption e_j. These two attributes pin down the car's driving range.

Lastly, the problem depends on the geographical location g of the car owner/ potential buyer and time period t which both affect the electricity rate from home and public charging. Both of these electricity rates potentially depend on the intraday period s, Making electricity rates dependent on the intraday period allows for accommodating real-time electricity pricing. Brought together, an individual might face an electricity price of p^a_{sgt} for public charging and p^h_{sgt} for home charging, both measured in Euros per kWh. For our empirical application, we take that $p^a_{sgt} > p^h_{sgt}$ for all (s, g, t) which is motivated by the exertion of market power by public charging stations. Note that we have already made the assumption that the pricing of charging stations and electricity providers from home charging are symmetric within a given market defined by (g, t).

Lastly, we need to take a stand on the charging speed available. This is captured by E which defines the kWh charged in a period s. We assume that it is constant throughout the day, across individuals, and across charging stations. It also does not vary depending on whether it is a public or a home charger. This assumption is due to data limitations but can be relaxed in counterfactual applications.

We now present the charging model that derives the usage cost for each individual-market-EV combination. For the sake of 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 which is captured by the binary decision variable q_s. This decision affects the state variable B_{s+1} which captures the level of battery charge in kWh. The state variable transitions in the following way:

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

This equality holds for all $s = \{1, ..., S\}$. If the individual is driving in period s, i.e. $r_s = 1$ then there is no choice but the battery depletes by $m_s \times e$ which captures the energy consumption of the car for that trip. If the individual is not driving then $r_s = 0$ and she can either choose to charge $q_s = 1$ or not. The battery level stays the same if she is not charging and increases by E if charging.

There are some technical constraints on the battery level. The level cannot exceed the battery size R of the car and cannot be negative, which we formalize in the following way:

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

Lastly, we define a state variable k_s which captures a reward for having charged in the

previous period. Its transition is defined as follows:

$$k_{s+1} = \begin{cases} 0, & \text{if } q_s = 0 \\ k_s + 1 & \text{if } q_s = 1, \end{cases}$$

which again holds for all s. We summarize those three state variables by defining $\mathcal{Q}(s, B_s, k_s)$ as the set of q_s such that the three conditions above are satisfied. In words, those are the charging decisions that are both technically feasible and further satisfy the exogenous driving needs.

Let us now define the cost minimization problem that an individual without access to home charging faces. In that case, we are looking at individuals with $l = 0$.

$$V_s^{l=0}(B_s, k_s) = \min_{q_s \in \mathcal{Q}(s,B_s,k_s)} \Big[\mathbb{1}\{r_s = 0\} \times q_s \times p_s^a \times \min\{E, R - B_s\} - k_s + V_{s+1}^{l=0}(B_{s+1}, k_{s+1}) \Big].$$

This is the value function for a dynamic cost minimization problem over the finite horizon of S periods. In period S therefore the above value function is reduced as $V_{S+1}^{l=0}(B_{S+1}, k_{S+1}) = c$ for all feasible (B_{S+1}, k_{S+1}) where c is some constant and hence can be dropped. The above program can be solved by backward induction. The program captures the idea that individuals are forward-looking in the sense that they take their future driving needs and electricity rate differences into account 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 cost of the maximum amount of kWh that the car can be recharged within one period. This amount is naturally capped by the maximal battery capacity. This monetary amount is reduced by a reward for consecutive charging k_s and increased by the continuation value.

The minimization problem for an individual with access to home charging, i.e. l=1, is defined similarly:

$$V_s^{l=1}(B_s, k_s) = \min_{q_s \in \mathcal{Q}(s,B_s,k_s)} \Big[\mathbb{1}\{r_s = 0\} \Big(\Big(\mathbb{1}\{h_s = 1\} \times p_s^h + \mathbb{1}\{h_s = 0\} \times p_s^a \Big) \times q_s \times \min\{E, R - B_s\} \Big) - k_s + V_{s+1}^{l=1}(B_{s+1}, k_{s+1}) \Big].$$

This program has a similar structure in the sense that there is only a decision of charging or not if the individual is not driving. The only difference is that when not driving in a given period s, the individual might be exogenously 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. The rest of the problem remains the same.

We can solve this model for each individual-EV-market combination which gives us three different variables that we can plug into the demand model for cars. The variable

$A_{ijgt}^{l_i=0}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i)$ defines the monetary energy cost from optimal charging when the individual cannot charge at home. It is hence derived from the optimal charging patterns found by solving the dynamic charging model when $l = 0$. Similarly, we can define two variables $H_{ijgt}^{l_i=1}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i)$ and $A_{ijgt}^{l_i=1}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i)$ for individuals that can charge at home where the first one is the energy cost from home charging and the latter one is that of public charging.

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. Let us define the individual choice set of i as χ_i.

3.2 Car demand model

The exposition here follows the standard BLP model based on Berry et al. (1995). 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:

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

We generally allow for car characteristics x_{jgt}^k and car price p_{jgt} to enter with random coefficients that are based on observed and unobserved heterogeneity. ξ_{jgt} are car, engine type and market fixed effects and ϵ_{ijgt} is i.i.d. Type I extreme value distributed. 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 solely based on an average fuel price in a given market, the fuel consumption of the car, and the individual's aggregate driving need for 14 days. While this already 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.

It is defined in the following way:

$$\begin{aligned} G_{ijgt}^{EV} \gamma^{EV} = &\mathbb{1}\{l_i = 0\} \left[(\gamma_a^{l_i=0} + \gamma_{ad}^{l_i=0} d_{gt}) A_{ijgt}^{l_i=0}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i) \right] \\ &+ \mathbb{1}\{l_i = 1\} \left[(\gamma_a^{l_i=1} + \gamma_{ad}^{l_i=1} d_{gt}) A_{ijgt}^{l_i=1}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i) + \gamma_h H_{ijgt}^{l_i=1}(\mathbf{r}_i, \mathbf{h}_i, \mathbf{m}_i) \right]. \end{aligned}$$

The first line is the disutility from monetary electricity cost if the individual does not have the option to charge from home. As previously explained $A_{ijgt}^{l_i=0}$ is derived from the charging model. Its marginal effect has a constant component $\gamma_a^{l_i=0}$ and component that varies with the number of public charging stations per household d_{gt} which is $\gamma_{ad}^{l_i=0} d_{gt}$.

For individuals who can charge at home, there are two electricity cost variables, from public and home charging respectively, which are again derived from the charging model. We allow the disutility from public charging to again vary by d_{gt} but the marginal effect might generally differ for those that can home charge which can be seen in the superscript $l_i = 1$ of $(\gamma_a^{l_i=1}, \gamma_{ad}^{l_i=1})$. Secondly, the marginal disutility from home charging is captured by γ_h.

We allow all these parameters to differ as one would generally think that they do. We expect that $\gamma_a^{l_i=1} < \gamma_a^{l_i=0} < \gamma_h < 0$. The last inequality should hold as all variables here are costs. The marginal disutility from home charging should be lower than that of public charging (with public charging station density going to zero) as there are no frictions such as search cost for example. The marginal disutility from public charging should generally be higher for those that can home charge as they might be less familiar with public charging. Hence it is relatively more inconvenient for them to charge publicly. We also would expect the following inequalities to hold: $\gamma_{ad}^{l_i=0} > \gamma_{ad}^{l_i=1} > 0$. The marginal disutility from public charging should decrease when the network of charging stations expands. This positive effect will be less strong for those that can charge from home as it is less relevant for them.

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 decision of heterogeneous individuals. This aspect enters in a micro-founded way where we use the charging model to link important individual aspects to the EVs and market conditions in terms of electricity prices and charging networks. It naturally captures the indirect network effect of increasing numbers of public charging stations and the number of EVs being bought. We refine previous approaches by making the point that public charging station density affects predominantly the population of individuals who cannot charge at home.

The EV-specific component plus the information on the individual choice sets are further important for the status quo and counterfactuals. The observed individual heterogeneity allows us to derive which individuals have previously bought EVs and which ones will buy EVs when the market conditions change. In combination with the charging model, we can also make statements about when EV owners charge their cars intraday and how this might change counterfactually.

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 $\sigma_{ijgt}(\mathbf{w}_i, \mathbf{z}_i, \nu_i)$ which can be aggregated to model predicted market shares σ_{jgt}:

$$\sigma_{jgt} = \iiint \sigma_{ijgt}(\mathbf{w}_i, \mathbf{z}_i, \nu_i) \; dF_\nu(\nu_i) dF_{\mathbf{z}}(\mathbf{z}_i) dF_{\mathbf{w}}^g(\mathbf{w}_i),$$

where $\sigma_{ijgt} = 0$ if j is not in χ_i. The random variable ν_i captures unobserved heterogeneity and z_i are observed consumer demographics. This expression accounts for individual choice sets and the fact that the distribution of the individual heterogeneity relevant for the

charging model $\mathbf{w_i}$ differs by geographical region.

3.3 Public charging station entry model

The public charging station entry model is not yet fully derived and hence is only described in words here. We extend Springel (2021) and Remmy (2023) who take a symmetric entry model which enables them to relate the number of public charging stations in a market to the EV base which means to the total number of EVs registered. We have already made the point that for EV owners the public charging station network only really matters if they cannot charge at home. Conversely what matters for charging station entry is not the total EV base but rather the realized public charging demand which is mainly derived from those EV owners that cannot home charge. We make use of our public charging data from Hamburg and the fact that the potential demand for public charging differs by region mainly because of varying home charging availability.

We therefore have the novel feature that network effects in our model are between charging stations and actual public charging demand which is predominantly determined by the amount of EV owners that mainly charge publicly.

4 Estimation

This section discusses how we solve the charging model as well as how we identify and estimate the demand model for cars. Including the charging model adds additional challenges for identification and estimation that is beyond the scope of this draft.

From the mobility data, we observe $(\mathbf{r_i}, \mathbf{h_i}, \mathbf{m_i})$ directly per individual that owns a car for one day in five-minute intervals. We further observe the dwellings of those individuals and assume that all those that live in one or two-family houses can home charge while others cannot. Therefore, we derive l_i as well. For each individual, we further observe some demographics such as age and income which we bundle into z_i. Our geographical markets g are defined by the combination of a state and the type of county which can take four values: Either metropolitan, urban, mainly rural, or rural. In the mobility data set, we observe which individuals live in which location g. A time period t constitutes a year. Together with g it defines a market. In order to use the outcome of the charging model for the estimation of the demand model, we solve a heuristic version of the charging model for each individual and EV combination. We do so as it decreases the computational burden substantially in comparison to solving the dynamic model by backward induction. For that, we use information on average retail electricity prices per year and location and the same for rates at public charging stations. We complement this with information on energy consumption and battery size of all EVs registered in Germany. We make the assumption that all charging is done with an 11 kW charger. This gives all ingredients to solve the model.

We can simply avoid solving the dynamic model as under the status quo, there is virtually no real-time electricity pricing for home and public charging. The timing of charging only matters for the individuals in the sense that they have to charge in a way that they meet their individual driving demands. They are indifferent between charging at many different points in time but the amount of charging is uniquely identified by the model. As previously mentioned, the model features endogenous choice set restrictions for individuals who cannot satisfy their driving needs with certain EVs. The dynamic set-up is important as individuals need to take into account their future driving needs but it will become more important in counterfactuals where we intend to introduce real-time electricity pricing.

As we only need the predicted electricity cost from home and public charging and not the timing of charging for estimation we designed an algorithm of many different if-conditions to get those predictions avoiding solving the dynamic model.

This gives us the necessary input in order to define the indirect utility u_{ijgt}. As in the standard BLP model, we equate the model predicted market share $_{jgt}$ with the observed market share $s_{jgt} = \frac{q_{jgt}}{\mathcal{M}_{gt}}$ where the numerator is the number of registrations of car j in market (g,t) and the denominator is the market size. With the BLP contraction mapping, we can eventually derive ξ_{jgt} which, interacted with some instruments, establishes identification. While most car characteristics including the electricity cost variables should be plausibly exogenous and hence instrument for themselves, we think that both the car price and charging station density are endogenous.

It is standard to think of the price being endogenous due to the joint determination of prices in equilibrium between demand and supply. A similar point has been made in Springel (2021) and Remmy (2023) for charging station density as the potential entrants for charging stations take into account the number of EVs registered. As previously mentioned, we think that the endogeneity comes from potential entrants taking into account the number of EVs owned by those that charge publicly which is partially determined by our demand model for cars. Therefore, we need both instruments for prices and charging station density. For the former, we construct multiple cost shifters. First, we interact an index of steel prices with the weight of the car as well an index of plastic prices with the size of a car. For EVs and Hybrid cars, we specifically add the cost of lithium-ion batteries interacted with the battery size. More challenging is the construction of instruments for charging station density. We need an instrument that shifts charging station density but does not affect the EV base. This essentially restricts the instruments to those that shift the cost for charging station operators. Here, we have collected the number of outages at the state and year levels. Also, we measured the distance of the geographical markets to the next transformation station which should reduce the connection cost of charging stations. This varies at the county level. Lastly, we have also information on subsidies for public charging stations which vary at the state and year level.

Another comment should be made about the variation that identifies the parameters of

the disutility from charging. Clearly, the variable itself varies by car and over time due to different electricity prices. The main variation, though, comes from geographical variation in charging station densities, electricity prices, and the composition of the population of individuals we integrate over. There are for example large differences in home charging availability and kilometers driven based on regions that we can exploit.

As previously mentioned, we will not discuss the charging station entry model at this stage. It is noteworthy that this will make identification and estimation more challenging as it involves estimating the public charging demand. Charging demand, EV demand, and charging station density are all jointly determined forcing us to find a way to identify a three-way simultaneous equation model.

5 Results

Work in progress...

6 Counterfactuals

Our model allows us to consider a rich set of counterfactuals in which we can study the effects of different policies on individual EV adoption, charging behavior, and intraday electricity demand from charging. Our micro-founded charging model allows us to study the impact of different policies on optimal charging behavior. The charging decisions will affect substitution patterns, allowing us to study who buys an EV and how many people buy EVs because of different policies. Knowledge on the overall EV uptake and their underlying usage allows us to predict counterfactual intraday load profiles and, in consequence, the impact on emissions and electricity costs. We plan to consider three counterfactuals.

In the first counterfactual, we evaluate the effects of purchase subsidies. Such a subsidy makes EVs cheaper for all driver types. Unlike previous studies, feedback loops from indirect network effects will depend on the additional local demand for public charging induced by the purchase subsidy. Previous studies assumed each EV increases demand for public charging by an equal amount. In areas where people mainly charge at home additional EVs will mainly charge at home. In consequence, the additional demand for public charging will be small, meaning network effects will be small. However, these areas are also likely to be the ones where purchase subsidies are most effective. When home charging is available, the main obstacle to EV adoption is the price difference between conventional and electric cars, which the purchase subsidy reduces. We would expect purchase subsidies to be most effective in rural areas. In consequence, such a purchase subsidy is likely to increase electricity demand at night.

In the second counterfactual, we evaluate the effects of subsidizing public charging

station entry. The resulting increase in public chargers will have a differential effect on EV users. Users that cannot home charge will see their disutility from buying an EV go down, whereas users with the ability to home charge will not see their utility from buying an EV affected. Again, this means that we will measure more realistic network effects compared to the previous literature that assumed each additional charging station affects all consumers in the same way. We expect that subsidizing charging station entry mainly leads to additional EV uptake in urban areas where many users rely on public charging. Since public charging occurs predominantly during the day, we expect such a subsidy increases electricity demand during the day.

In the third counterfactual, we plan to evaluate the effects of introducing time-varying electricity prices. Such a pricing scheme would incentivize users to charge outside of peak hours. Day-time charging would likely become more expensive, shifting electricity demand from EVs behind the evening peak into the night. Such a scheme, while easing the strain on the grid and reducing peak prices, may lead to the bulk of charging occurring after the sun has gone down and solar PV generation has retired for the day. Such a scenario could uncover interesting interactions between electricity demand and renewable-induced supply shifts. On the one hand, charging may now occur when demand for non-EV-related electricity is low. On the other hand, charging may now occur when the renewable share is relatively low.

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