Price Discrimination in Electric Vehicle Fast Charging

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Abstract

This paper studies the interaction between market power and price discrimination in the German electric vehicle (EV) fast charging market. Large charging networks use two-part tariffs in the form of subscription plans to price discriminate based on consumers' expected charging needs. Using novel, high-frequency fast charging data, rich consumer microdata, and large-scale commuting and mobility data, I estimate a structural discrete choice model of spatial charging demand. Consumers are heterogeneous in their routes, alternative charging options, and preferences for charging speed. Consumers choose whether to subscribe to a plan based on their expected charging needs. Using my model, I conduct counterfactual scenarios to decompose the effect of network structure and price discrimination on market power. I find that eliminating price discrimination causes prices to decrease by 9.0% on average, while aggregate demand increases by 5.5%. Demand reallocates from networks which engaged in price discrimination to those that did not. While most consumers experience lower charging prices after banning price discrimination due to increased competition, a small subset of consumers experience an increase in charging costs. I also find that price discrimination exhibits complementarities with network structure and allows networks to capitalize on advantageous positions.

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1 Introduction

As of July 2026, electric vehicles (EVs) comprised 29.3% of new car sales in Germany, with EVs representing 4.1% of the current vehicle fleet (KBA 2026). The German government has committed billions of dollars in subsidies to accelerate the EV transition, and the European Union has sought a 90% reduction of tailpipe CO_2 emissions by 2035 (Reuters 2025). Fast charging infrastructure - which enables charging in minutes, rather than hours - is a critical component of this transition. Fast charging enables en-route charging and mitigates the fear of running out of charge before reaching one's destination (ACEA 2024). In order for fast charging to effectively accelerate the EV transition, it must be both accessible and affordable.

My paper concerns the German market for public fast charging. In this market, charge point operators (CPOs) sell charging to consumers through networks of charging stations. CPOs are differentiated by network size, location, and station quality. One notable feature of this market is that the entry of charging stations at Autobahn service areas was restricted to a select few firms. This facilitated network development along key routes. However, it also sparked concerns about competition and market power. The German Monopoly Commission expressed their concern that this allocation gave the selected CPOs excessive market power and limited competition along the Autobahn.[1] Other networks (Tesla and Fastned) filed a lawsuit in 2022, sparking a lengthy legal battle culminating in a 2026 ruling that the non-competitive allocation was indeed illegal. Any future Autobahn service area stations must now be allocated using a competitive tender process.

How much market power did this illegal allocation create? In this setting, market power operates through two channels: spatial differentiation and price discrimination. Spatial differentiation contributes to market power since a driver's location determines which stations are available to them. Instead of considering all stations in a market equally, they are more likely to consider those which are nearby. The spatial nature of demand, combined with the fact that most consumers face few local charging options, give CPOs market power. Furthermore, stations located in more desirable or convenient locations - e.g. close to the Autobahn or near popular amenities - will attract more consumers. CPOs which are able to secure advantageous locations will enjoy additional pricing power.

CPOs also gain market power through price discrimination. Most CPOs in the German market set network-wide prices which do not vary either by time or location. In contrast, certain large CPOs (EnBW, Ionity, and Aral Pulse) offer optional subscription plans which give consumers cheaper charging prices in exchange for a fixed subscription fee. These subscription plans operate as a two-part tariff and are targeted towards heavy charging consumers. A driver will benefit from such a plan if they do a sufficient amount of charging at the selected network. This also suggests complementarities between network structure and price discrimination: doing most of one's charging at one network is much easier if the

[1] https://www.monopolkommission.de/publikationen/energie/sektorgutachten/energie-2025-wettbewerb-und-effizienz-fuer-ein-zukunftsfaehiges-energiesystem

network is very dense and convenient to access.

How do network structure and price discrimination interact to create market power? To answer this question, I estimate a spatial discrete choice model of charging demand in the style of Berry, Levinsohn, and Pakes 1995 using novel real-time charging demand data from Germany. I also leverage detailed survey microdata from German EV drivers as well as large-scale commuting and mobility data. In my model, each consumer must complete a designated number of charging events. On each charging event, drivers choose between fast charging stations along their route and slow charging options (home, work, or public slow charging). In the vein of Houde 2012, the set of public fast chargers available to the consumer, as well as their charging needs, are influenced by their location and regular driving routes. The convenience of a charger depends on the detour the consumer must incur to access it. Additionally, I allow consumers to differ in their available alternative charging options of home and workplace charging. Drivers optionally pick a subscription plan to maximize their expected utility from charging. I assume that CPOs set prices and fees to maximize static charging profits.

On the supply side, CPOs are differentiated in terms of station characteristics and location. CPOs set network-wide charging prices and plan fees to maximize static profits under the assumption of Bertrand-Nash competition. I do not model entry of new stations in this model, and I abstract away from dynamic considerations. I estimate my model using a GMM objective function which incorporates observed charging demand, rich micro data, and supply-side moments.

I find that consumers are sensitive to charging price, with an average station-level price elasticity of -1.79. This is comparable to experimental estimates found by Bernard et al. 2025. I find that consumers who cannot charge at home or work tend to be the least elastic, while consumers who have these alternative options are the most elastic. My model rationalizes the immense heterogeneity in charging behavior across consumer types. Consistent with the micro data, I find that consumers with access to charging at home or work do far less public charging than those who have neither option. Additionally, I replicate the fact that heavy driving consumers are more likely to use public fast charging. My model also yields intuitive substitution patterns: consumers with faster charging vehicles pick faster charging stations, while those with slower charging vehicles pick slower stations.

Using my model, I conduct a series of counterfactual scenarios to isolate separately how network structure and price discrimination contribute to market power. First, I ban price discrimination and only allow CPOs to set one linear price for all consumers. Second, I simulate the effect of changing market structure by randomly swapping locations of the plan-offering networks with locations of other networks, while still allowing these networks to offer plans. Finally, I combine these two scenarios by both changing network structure and banning price discrimination.

I find that banning price discrimination causes a sales-weighted average price reduction of 9%. The aggregate quantity of charging increases by 5.5%. Demand reallocates from plan-offering CPOs (−3.98%) to non-plan CPOs (+13.4%). Profits decrease by 18.2% for plan-offering CPOs and by 3.2% for non-plan CPOs. On the consumer side, I find that the vast majority of consumers benefit from the elimination of price discrimination. While a small number of plan consumers pay higher prices (now that they can't access discounted rates), this is mostly offset by price reductions of other networks. In summary, price discrimination acts to soften competition and enhance market power.

Turning to the network structure permutation scenario, I find that prices for plan-offering CPOs decrease by an average of 4.3% and increase slightly for non-plan CPOs by an average of 0.79%. In other words, this intervention acts as a transfer of market power between plan-offering CPOs and non-plan CPOs. Non-plan networks experience increased demand and profits afforded by their new, advantageous locations, to the detriment of plan-offering networks (which lost advantageous locations).

I finally consider the same station reallocation but also shut down price discrimination. This combined intervention intensifies the effect of banning price discrimination: plan-offering CPOs reduce their linear prices even more and experience even lower profits than in the standalone plan elimination scenario. This suggests complementarities between network structure and price discrimination: the impact of losing advantageous network structure is worsened when firms are not allowed to price discriminate. Or, in other words, advantageous network structure enhances the gain from price discrimination.

1.1 Related Literature

One major contribution of this paper is to study price discrimination in two-part tariffs within an asymmetric oligopoly setting. There is an extensive literature on price discrimination. Theoretical contributions about the welfare implications of third degree price discrimination in a monopoly setting include Robinson et al. 1969, Varian 1985, and Aguirre, Cowan, and Vickers 2010. A comprehensive survey can be found in Stole 2007. In an oligopoly setting, relevant papers include Holmes 1989, and Corts 1998. Empirical papers examining third degree price discrimination in oligopoly settings include Borenstein and Rose 1994, Asplund, Eriksson, and Strand 2008, Gerardi and Shapiro 2009.

While third degree price discrimination has been studied extensively, there has been far less analysis of competition in two-part tariffs in an oligopoly setting. Competition using two-part tariffs in oligopoly has been studied in a theoretical context by Armstrong and Vickers 2001, Rochet and Stole 2002, Yin 2004, Griva and Vettas 2015, and Tamayo and Tan 2021. On the empirical side, relevant papers include Miravete and Röller 2004, Miravete 2005 (monopoly) and Davies, Price, and Wilson 2014 (oligopoly). My paper contributes to this literature by studying competition in optional two-part tariffs when both consumers and firms are heterogeneous and only some firms price discriminate.

My paper also contributes to the growing literature related to electric vehicles and charging infrastructure. This includes a number of works which have modeled the complementarity between charging infrastructure and EV adoption (S. Li et al. 2017, Springel 2021, J. Li 2023, Remmy 2026), consumers' demand for EV charging stations (Dorsey, Langer, and McRae 2025, Barwick, S. Li, and Xia 2026), and the price sensitivity of charging demand (Bailey et al. 2023, Metcalfe et al. 2026, Heid, Remmy, and Reynaert 2025, Bernard et al. 2025).

Most papers discussing the price sensitivity of EV charging demand focus on the temporal aspect of demand, highlighting consumers' responsiveness to time of use pricing and their willingness to shift charging to off-peak times. In my setting, this is less relevant: the price of fast charging almost never varies by time of day, with networks offering fixed prices per kWh. Additionally, while Bernard et al. 2025 estimates price sensitivity for public charging using a large-scale randomized control trial, they do not model consumers' station choice.

My paper contributes to this literature by estimating demand for EV fast charging using a novel dataset of real-time charging data for virtually all fast chargers in Germany. Given the distinct lack of publicly-available fast charging demand data, there has been little empirical work examining fast charging. By estimating key demand charging demand parameters, my paper contributes to our understanding of the demand for fast charging. Additionally, since my model incorporates multiple dimensions of consumer heterogeneity, I can compare how demand and substitution patterns vary based on consumer type. This allows me to analyze the distributional effects of price discrimination.

2 Background and Data

Electric vehicles operate by using electricity stored into a battery to power their engine, similar to the role of fuel in an internal combustion vehicle. Instead of refueling a tank of gas, an electric vehicle's battery must be recharged using electricity. To charge an electric vehicle, the driver must simply plug a charger into the vehicle.

Electric vehicle charging takes a variety of forms. It may either occur at a private charging point (e.g. in home or at the workplace) or at a public charging station (in parking lots, parking garages, stores, or standalone charging stations). The main distinction is between alternating current (AC) and direct current (DC) charging or, in other words, between slow and fast charging. AC charging refers to when the vehicle receives alternating current electricity from a charger. This electricity is subsequently transformed into direct current using an on-vehicle transformer, after which it goes into the battery. AC charging is slow and may take between a few and several hours to fully charge a vehicle's battery. Consequently, AC charging is suitable to situations where drivers park their vehicle for long durations: home, the workplace, or conveniently-located long-term parking spots.

DC charging, on the other hand, converts the AC power from the grid to DC power within the charging station itself, allowing the charger to supply electricity directly to the vehicle's battery. The transformer in a charging station is much more powerful than the one embedded in the vehicle, making DC charging orders of magnitude faster than AC charging. Instead of taking hours to charge, an EV can charge a majority of its battery within a span of 15 to 30 minutes. As such, DC charging is commonly referred to as 'fast' charging and AC as 'slow' charging.

DC charging is suitable for charging on the go, allowing consumers to charge rapidly and continue on their route. DC fast charging stations are more commonly found along highways and primary roads. Fast charging stations are also considerably costlier to install than slow charging stations, mainly due to the higher complexity of the equipment, costly grid upgrades, additional permitting processes, and other factors. A slow charging station may cost a few thousand euros per charger to install, whereas a fast station can easily cost tens of thousands of euros for the charging equipment alone in addition to any installation costs. It is not uncommon for total investment costs to exceed hundreds of thousands of euros per station, while larger stations with several chargers may cost over a million euros.

This paper focuses on fast charging. A fast charging station is similar to a gas station: it has a collection of chargers, just like a gas station has multiple pumps. This enables multiple consumers to use a particular station at the same time. If a consumer wants to charge, they drive up to the charger, initiate the session (commonly using a dedicated charging card or app, less commonly a card reader), and plug in their vehicle. Similar to gas stations, consumers decide how much charging they want to do and terminate the charging event by unplugging their vehicle from the charger.

The operator of a charging station is referred to as a Charge Point Operator (CPO). A given CPO may operate a number of fast charging stations that constitute a *charging network*, similar to how a gas station brand may operate multiple locations. I will use the term network and CPO interchangeably throughout this paper with the understanding that the CPO refers to the operator of a given charging network.

As a brief aside on electricity terminology: the main two terms I will use throughout this paper are kilowatt (kW) and kilowatt-hour (kWh). A kilowatt is measure of rate and corresponds to the rate of electricity usage or delivery. A kilowatt-hour corresponds to the quantity of electricity used/transmitted by one kilowatt of power over the course of an hour. In other words, kilowatt is a measure of flow while kilowatt-hour is a measure of stock. Charging speeds are represented in terms of kilowatts, while charging amounts and battery sizes are discussed in terms of kilowatt-hours. For brevity, I will abbreviate both by their respective unit symbols (kW and kWh) throughout this paper.

Each charger within a fast charging station may offer a different speed of charging, with speeds commonly ranging from 50 to 350 kilowatts (kW). The charging speed refers to the maximum rate of power delivery (measured in kW). To put these values in context, a vehicle with a 50 kWh battery charging from 20-80% (i.e., 30 kWh of charging) would take 36 minutes at a 50 kW charger and 10 minutes on a 300 kW charger (assuming that the vehicle is able to handle the charging speed).

Faster charging speeds enable faster charging, but not all vehicles can realize such speeds. Vehicles differ in their maximum rate of charging acceptance for a variety of reasons (voltage, battery chemistry, the on-vehicle transformer, and other engineering considerations). Vehicle charging speeds may range from less than 50 kW to nearly 250 kW, while the existing German fleet has an average charging speed of approximately 116 kW. The realized charging speed is the minimum of the station's speed and the vehicle's maximum charging speed. The upshot is that a consumers' charging speed determines the extent to which they care about differences in station charging speed: a 50 kW vehicle sees no difference in charging time from using a 350 kW charger vs. a 50 kW charger, while a 250 kW vehicle charges nearly five times faster on a 350 kW charger compared with a 50 kW charger. Charging speed is thus an important dimension of differentiation for certain consumers, but may be far less important to others.

Additionally, the speed of charging varies over the course of the charging event. Charging is fastest when the battery is empty and slows down as it fills up. The speed slows dramatically when the battery is mostly full. It often takes a similar amount of time to charge from 20-80% as it takes to charge the remaining amount from 80-100%. Consequently, EV drivers at fast charging stations tend to charge their vehicle most - but not all - of the way.

As alluded to previously, this market differs from the gasoline market in another major way: most charging stations do not have credit card readers. Rather, they require consumers to either pay through the app, use a dedicated near field communication (NFC) charging card, or some other form of payment. This is changing as a result of the EU's 2024 AFIR law which mandates, among other things, that all newly-installed fast charging stations be equipped with a card reader (and that existing stations be retrofitted by 2027). To pay for charging, consumers generally use a physical charging card or app. For example, if a consumer wants to charge at EnBW, they may use the EnBW app. If they want to charge at Ionity, they may use the Ionity app. It is not uncommon for consumers to have multiple apps installed on their phone so that they can access multiple providers.

On the topic of payment, I now discuss the structure of charging prices. Prices for public charging are set by each charging network. Virtually all networks at the time of my sample set uniform prices across the entire country - that is, almost all networks have no spatial (or temporal) variation in prices. This is in contrast both with the market for gasoline (where prices are spatially differentiated) as well as the market for electricity (where prices vary based on time of use). Some networks set prices on a country-by-country basis, but very few set prices on a more granular level.

Most CPOs simply set one price, which I will refer to as the *basic price*. That is, a per-kWh charging price available to all consumers without any monthly subscription. This price can be obtained usually by paying through the provider's own app (or card). Often, the consumer must set up a free account with the provider as well. As an example, consumers can charge at an EnBW station for €0.59/kWh so long as they download the EnBW mobility+

app and create a free account.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.39	0.58	0.61	0.61	0.65	0.79

Table 1: Summary statistics of basic prices as of September 2024. Values are prices in Euros per kWh.

Table 1 summarizes the distribution of basic prices for networks in my sample. The values in the table represent the price in Euros per kWh charged. The average price is €0.61/kWh. Prices are relatively tightly dispersed, with the difference between the third and first quantiles being seven cents. Nevertheless, the overall range of prices is relatively large, with prices ranging from a minimum of €0.39 to a maximum of €0.79. At the lower end, a few other grocery chains offer comparatively low prices: Aldi South (€0.39/kWh), Lidl (€0.44/kWh) and Kaufland (€0.44/kWh). This can be understood as a subsidization strategy, where discounted charging can entice consumers to charge while visiting their store.

It is also possible for consumers to charge 'ad-hoc'. Ad-hoc charging allows consumers to pay directly for charging without creating an account with a provider. While convenient, this option tends to be significantly more expensive than even the basic price. For example, EnBW charges €0.87/kWh for ad-hoc charging vs. €0.59/kWh for basic. Similarly, Aral charges €0.79/kWh for ad-hoc charging vs. €0.61/kWh for basic. The only difference to the consumer is that they don't have to create a free account if charging ad-hoc. I assume that consumers do not pay the ad-hoc price and instead pay the provider's basic price. This is consistent with both consumer surveys as well as industry anecdotes.

However, some CPOs don't just set one price. As promised in the title of this paper, some networks engage in price discrimination using menus of two part tariffs. These two-part tariffs take the form of subscription-based monthly plans which allow consumers to charge at discounted prices in exchange for a monthly fee. Such plans are suited for drivers with higher expected charging demand and allow them to reduce their per-kWh charging costs in exchange for an upfront lump-sum payment.

For example, EnBW offers consumers two paid subscription tiers. One plan offers a charging cost of €0.49/kWh in exchange for a monthly fee of €5.99. The other plan lowers the charging cost to €0.39 with a monthly fee of €17.99. The former plan is advantageous if consumers do greater than one charging event at an EnBW station. The latter plan is preferred if the consumer does at least four charging events at EnBW stations.

Table 2 summarizes the charging prices and monthly fees for plans from EnBW, Ionity, and Aral Pulse. It also lists the basic price of each network for comparison. Paid plans offer a significant reduction in charging costs: subscribing to the €5.99/month plan for EnBW reduces per-kWh charging costs by approximately 17%, while the €17.99/month plan reduces charging costs by 33%. The €5.99/month plan from Ionity reduces prices by around 28%, while the €11.99/month plan offers an approximately 43% reduction. Subscription plans offer significantly lower charging costs for consumers with heavy charging needs.

	Price (€)/kWh	Monthly fee (€)
EnBW	0.59	0
	0.49	5.99
	0.39	17.99
Ionity	0.69	0
	0.49	5.99
	0.39	11.99
Aral	0.61	0
	0.57	4.5[2]

Table 2: Per-kWh prices and monthly plan fees for the largest subscription providers. All values are in Euros. The first column represents the price per kWh charged. The second column represents the plan fee, with 0 indicating that there is no cost of subscribing.

It is also possible for consumers to utilize roaming plans, which allow them to access a variety of providers through a single card or app. Instead of having a separate account and app for each provider, consumers would instead only need one card/app for all of their charging. Historically, roaming plans offered a uniform price *regardless of network*, with some specific exceptions. Such plans were quite popular in the early days of electromobility, but their attractiveness has waned as rising charging costs drove up roaming prices. During the sample period, the cost of accessing a network through roaming is often much higher than that provider's own price. As it is usually a dominated option for consumers and I do not observe data on roaming utilization necessary to model roaming, I do not include roaming in my model.

Finally, while the vast majority of charging networks utilize uniform spatial pricing, one exception is the Shell Recharge network. During the sample period, prices at Shell Recharge stations ranged between €0.57-0.64/kWh, depending on the station's location. As I don't observe the effective station-specific price, I assume consumers pay €0.61/kWh, which represents the midpoint of the price range.

2.1 Charging demand

I construct a novel dataset of real-time station utilization data for the vast majority of German EV fast charging stations. This dataset includes all stations which publish real-time information through the Open Charge Point Interface (OCPI) API. My data ranges from November 2023 until November 2025. However, for the purposes of the present analysis, I will be analyzing demand from September 2024. Figure 13 in the appendix contains a map of all of the charging points in my sample.

Notably, this data does not include the Tesla Supercharger network. The Supercharger network is available to all EV drivers, but unfortunately does not make data available via the

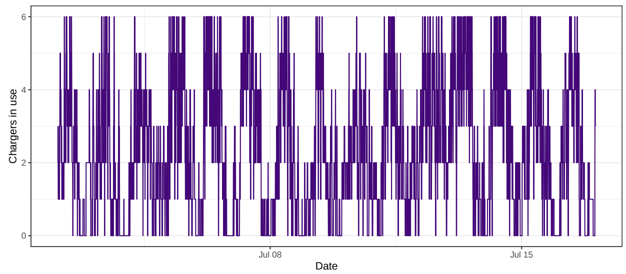


Figure 1: Example of charging demand data from an Ionity fast charging station over a two week period in July 2024

OCPI. This makes scraping real time information significantly more challenging. I thus omit the Supercharger network from my analysis.

I scraped the data in real time at approximately three-minute intervals. In each round of scraping, I observe the number of available charging points at a given station. An example of this data for a single station is provided in 1. As I observe the number of available charging points over time, I gain a high-frequency profile of charging behavior at the station and can back out the number of charging events that occur. I define a charging event as a decrease in the number of available charging points within a station between two consecutive time periods.

I now provide a summary of the major players in the German EV fast charging market. Table 3 lists the top 10 CPOs in the German market as of September 2024, sorted based on aggregate charging demand. It also presents the number of charge events per station, the network's aggregate market share, and its number of stations. CPOs can generally be classified into four major categories: public utilities and power providers (EnBW, EWE, E.ON), oil and gas majors (Aral Pulse and Shell), grocery (Lidl, Kaufland, ALDI South), and pure-play providers (Ionity and Allego).

Network	Stations	Ports/stat.	Share	Dem/stat.	€/kWh	Power (kW)	Autobahn
EnBW	1355	4.71	0.22	380.38	0.59	220.63	0.34
Aral	426	7.23	0.10	544.85	0.61	253.76	0.46
IONITY	147	7.45	0.07	1037.51	0.69	352.72	0.93
EWE	575	2.41	0.05	205.28	0.59	197.76	0.35
Lidl	446	2.36	0.04	217.38	0.44	56.88	0.19
Shell	338	3.78	0.04	277.83	0.61[3]	263.83	0.36
Kaufland	314	2.52	0.04	279.98	0.47	55.74	0.18
Allego	404	3.85	0.03	192.54	0.73	168.07	0.52
E.ON	314	2.75	0.03	208.43	0.61	113.34	0.73
ALDI	236	2.17	0.03	277.31	0.39	125.28	0.40

Table 3: Summary statistics for the top 10 networks ordered by aggregate network charging demand during September 2024.

Two things are worth noting in this table. The first is the asymmetry in size between

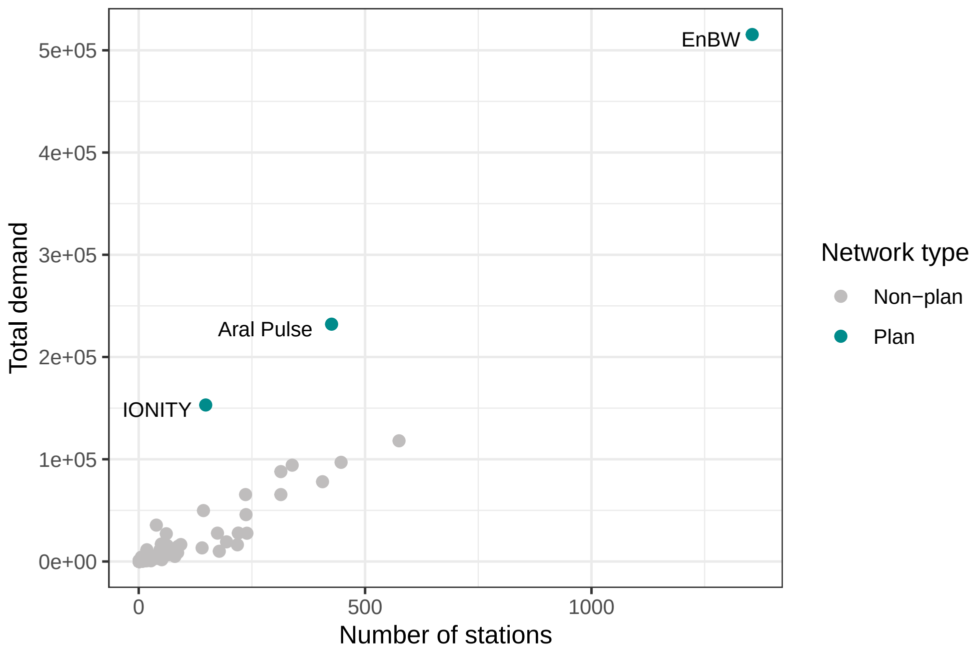


Figure 2: A scatter plot of network demand (number of charging events) versus network size. Plan networks are indicated with cyan dots and are labeled on the graph. Non-plan networks are plotted in grey.

different networks. The largest, EnBW, is a large utility company that operates a nation-wide network of 1,367 stations. The smallest is Ionity, a joint venture of several automakers, with 149 stations. While Ionity is the smallest of the top 10 in terms of station count, its locations are almost entirely located along the Autobahn and other major highways.

The second main takeaway is the vast difference in utilization (charging events per station) between the top three networks (EnBW, Aral Pulse, and Ionity) vs. the others. Each of these networks has significantly higher charges per station than other networks. The disparity is more clearly visible in Figure 2, which plots the network size on the horizontal axis and charging demand on the vertical axis. EnBW, Aral Pulse, and Ionity receive an outsized shares of charging demand compared to networks of similar size.

What explains this large difference in utilization relative to rival networks? I'll argue that there are three major factors: speed, location, and price discrimination. As can be seen in Table 3, these networks are some of the fastest in the top 10. In the appendix, Table 12 summarizes the maximum power available at stations within each network, and Table 13 summarizes the distribution of port-level charging speeds for each network. EnBW, Aral, Ionity, and Shell tend to have the fastest chargers (each having at least a majority of stations with max power at least 300 kW), while other networks in the top 10 have median speeds of either 50 or 150 kW. This shows that there is a large degree of speed differentiation between networks. However, it's not just a speed story, as Shell has far lower utilization than the top three networks.

Location quality also plays a large role in differentiating CPOs. Each of these three networks are widely available and located at convenient, high-traffic areas. EnBW and Ionity, for instance, are two of the four providers which operate chargers at Autobahn service areas. Aral Pulse also offers chargers at its gas station forecourts directly adjacent to Autobahn service areas as well as an extensive network of truck stops along major highways. While Ionity has significantly fewer locations, they are more strategic in their site choices and tend to build fewer locations and target higher-utilization locations.

Fast charging stations near the Autobahn account for an outsized share of total fast charging. While they account for only 32 percent of total stations, they account for nearly half (49%) of all charging. Table 4 compares station utilization across three different location types: non-Autobahn locations, stations located within 1km of the Autobahn but not located at a service area, and locations located at an Autobahn service area.[4] Breaking this down further, we can see that chargers at Autobahn service areas are responsible for 20 percent of overall charging demand while representing merely 8 percent of all stations. Additionally, the average per-station daily number of charges at stations in Autobahn service areas (20.02) is more than double that of Autobahn-adjacent stations not at service areas (9.48) and more than three times higher than non-Autobahn stations (5.86). Chargers at convenient locations situated along key routes experience far higher utilization than other stations, even those located along the same highways. It is not surprising that EnBW, Ionity, and Aral Pulse tend to have higher utilization given their presence along these key routes.

Location	Stations	Charges/day/station	Station share	Charging share
Non-Autobahn	6672	5.86	0.68	0.51
Autobahn (not service area)	2316	9.48	0.24	0.29
Autobahn (service area)	765	20.02	0.08	0.20

Table 4: This table compares station demand from September 2024 based on location type: non-Autobahn chargers (located more than 1km away from the Autobahn), chargers located within 1km of the Autobahn but not located at a service area, and chargers at an Autobahn service area.

The final potential explanation for this higher utilization is that each of the top three networks engage in price discrimination through menus of two-part tariffs. These networks offer monthly subscription plans in which consumers receive discounted charging prices in exchange for a fixed monthly fee. These plans will be worthwhile for consumers if 1) the consumer has heavy charging needs and 2) they can feasibly do most of their charging at the selected CPO's network. Once a consumer has selected a plan, all else held equal, they will have incentive to do most of their charging within that CPOs network. This gives them an advantage in utilization relative to other networks. Of course, these two factors are not mutually exclusive - in fact, they likely amplify each other. The fact that these CPOs have

[4]An Autobahn service area is located right off the Autobahn, similar to a rest area. Service areas feature parking, amenities such as restaurants, convenience stores, and restrooms.

locations at key locations along the Autobahn and road network enhances the attractiveness of their subscription plans.

2.2 USCALE driver survey

A central feature of the EV charging market is the large degree of heterogeneity on the part of consumers. Some drivers can charge at home or work, while others cannot. Some are highway drivers while others are city drivers. Consumers differ in their location and regular driving routes and thus have different choice sets. Some drive 5,000 km, whereas others drive upwards of 25,000 km. Some can charge faster, while others charge much slower. All of these factors influence 1) how frequently consumers need to charge, 2) how often they charge in public, and 3) which chargers they choose to charge at.

My goal - a bit of a lofty one - is to develop a model which incorporates each of these dimensions of heterogeneity. Such a model will rely heavily on data which can speak to the rich variation in consumers' types and charging behavior. To address this need, I use detailed survey data from USCALE, a German company which specializes in surveys regarding electromobility.[5] Specifically, I use USCALE's 2024 Public Charging Study as my main data source to model the distribution of consumer types. The Public Charging Study is a survey of 2,986 German EV drivers. The survey was conducted online from July-September 2024. As a supplement, I also use the 2024 eMSP Loyalty Benchmarking Study, which was conducted in September 2024.

The Public Charging Study contains a wealth of information about consumers and their vehicle. The survey reports coarse levels of consumer demographics, including their federal state, income bin, age, residence type (single vs. multifamily home, rent vs. own, parking availability), and city type. I also see key information about consumers' vehicle. Namely, I observe the EV make and model, EV range (binned), battery size (binned), and maximum charging speed (binned).

Crucially, the survey also contains information on consumers' driving and charging behavior. For driving behavior, I see binned average daily commute distance and binned annual mileage. I observe which location types consumers charge at (home, work, and public), what share of charging electricity comes from each, and how frequently they charge. This allows me to see how many people have access to charging at home and/or work. It also shows me how much they actually use each option when they are available.

Using this information, I construct consumer types based on the available outside options each consumer has. Consumers of type h have access to charging at home, but not at work. Similarly, consumers of type w have charging at work but not at home. Consumers of type hw have access to charging at both home and work, while consumers of type n have access to neither.

[5] https://uscale.digital

City type	P(Home)
Large city $>$ 1M	0.69
Large city $>$ 500k	0.74
Large city $>$100k	0.75
Medium city	0.80
Suburbs	0.84
Small city	0.86
Countryside	0.94

(a) Proportion of survey respondents with home charging, conditional on city type

City type	P(Work)
Large city $>$ 1M	0.47
Large city $>$ 500k	0.41
Large city $>$100k	0.36
Medium city	0.27
Suburbs	0.27
Small city	0.25
Countryside	0.19

(b) Proportion of survey respondents with work charging, conditional on city type

Table 3a summarizes the proportion of consumers who have access to charging at home, broken down by the type of city the respondent resides in. Table 3b does the same, but for work charging. The main takeaway is that the proportion of respondents with home charging decreases with the level of urbanization: 94% of respondents in the countryside have home charging, compared to only 69% in cities with over 1 million population. Conversely, the proportion of respondents with work charging is increasing in urbanization: only 19% in the countryside have it, compared with 47% in the largest cities.

Location	hw	h	w	n
Home	0.53	0.84	-	-
Work	0.31	-	0.60	-
Public fast	0.12	0.13	0.25	0.52
Public slow	0.05	0.03	0.15	0.48
N	421	1142	129	186

Table 5: Average charging energy shares at each location type, by consumer type. All values represent the average share of charging done at the designated charging location type.

This survey also includes valuable information about consumers' charging behavior. Table 5 presents the average share of charging done at each location type (home, work, public fast, and public slow) for each consumer type (hw, h, w, n). The main takeaway is that a consumer's type plays a key role in their charging behavior. Two main patterns of note are that 1) consumers do most of their charging at home or work, with home preferred, and 2) the more outside options available, the less consumers rely on public fast charging (and public charging, more generally).

Not surprisingly, consumers with access to home charging utilize it for most of their charging needs. The home charging share is 84% for type h, compared to 53% for type hw. Home charging is the most convenient option: users can simply plug in and leave the car until they are ready to drive. It is also usually cheaper than charging in public, making it generally consumers' first choice. This is in line with existing results that home charging comprises the majority of EV drivers' charging.

Similarly, work charging is frequently utilized by those who have access. For those with only work charging, 60% of charging is done at work. This decreases to 31% for consumers with home charging as well. The relative inferiority of work charging compared to home charging likely stems from two factors. First, home charging is simply more commonly available: work charging is only available after driving to work, whereas home charging is available even on non-work trips. Second, there may be true differences in work charging attractiveness (price, availability, reliability) which affect consumers' choices. There could also be a limited number of chargers shared by employees. Type w drivers who have charging only at work do not do not rely on work charging as much as type h consumers rely on home charging. The story here is similar: while work charging may be an attractive option, it cannot be accessed on non-commuting trips. Consequently, these drivers must rely on public charging sources to fulfill their remaining charging needs.

Turning to public charging, the reliance on public charging (either slow or fast) decreases with the attractiveness and quantity of outside options. The fast charging share is highest for type n (52%) and type w (25%), and it is lowest for type h (13%) and hw (12%). This is not surprising: the more alternatives a consumer has, the less they likely require fast charging to complete their route. Similarly, the share of slow charging decreases from 48% for n types to 15% for w, and 3% and 5% for types h and hw, respectively.

Type n consumers with neither home or work charging split their charging roughly evenly between slow and fast public chargers. Slow charging functions in a similar way as home or work charging, but is less convenient to access: if it is not located near their home or destination, its attractiveness is limited. If the closest slow charger is a 15 minute walk from their home/destination, consumers would incur 30 minutes of walking (round trip) to charge there. In the same amout of time, they could use a fast charger and remain in the comfort of their vehicle. It is thus not shocking that type n relies the most on fast charging among the four types. Even though consumers have to drive to the charger and wait while their car is charging (unless it is at the destination), the speed of charging is significantly faster.

I also find that the ratio of public fast to slow charging increases as consumers' outside options improve. The intuition for this is simple: public slow charging is more closely substitutable with home or work charging than fast charging. Such options are used when they are available and convenient. Fast charging, conversely, is commonly used in more urgent situations where consumers have insufficient range to get to an alternative (home/work/slow). When one is on the motorway 40 km away from home with a low battery, it is not possible to use home charging (barring a behemoth charging cord). In this instance, they must rely on fast charging.

Consumers' charging behavior is also governed to a significant degree by their driving behavior. Table 6 lists the share of public fast charging separately for each consumer outside type and binned annual mileage. Annual mileage is separated into bins of 10,000 km.

Mileage bin (km)	hw	h	w	n	N
(0, 10,000]	0.08	0.08	0.20	0.54	459
(10,000, 20,000]	0.12	0.14	0.24	0.48	961
(20,000, ∞)	0.14	0.19	0.32	0.63	458
N	421	1142	129	186	1878

Table 6: Public fast charging share, by consumer outside option type and annual mileage bin. Mileage is binned into 10,000 km bins. Values refer to the share of public fast charging done by consumers of the indicated type and annual mileage bin. The bottom row indicates the number of consumers of each type, whereas the final column indicates the number of consumers in each mileage bin.

The fast charging share is monotonically increasing in mileage (with the exception of type n, which exhibits non-monotonicity). For most consumers, more driving correlates with a higher share of charging electricity done at public fast charging stations.

This is intuitive - when consumers drive more, they are putting themselves in more situations where they find themselves in need of charging. For someone who seldom drives except for a trip to the grocery store, there is little chance of finding oneself at a dangerously low battery level and insufficient range to get home. It is rare that they would need to rely on a fast charger. Compare this with a driver that has a heavy commute and likes to take day trips regularly. This frequent driver is more likely to find themselves in a situation where they need to charge while on the go, even if they have a perfectly fine option at home or work.

High-mileage types also account for a disproportionate share of total fast charging demand. Consider the example of type h. These consumers have access to home charging and will generally use that as their first choice charger. Nevertheless, their dependence on fast charging increases with their annual mileage. Drivers with mileage over 20,000 km have a fast charging share of 19%, compared with merely 8% for drivers with mileage under 10,000 km. Additionally, consider the fact that high mileage drivers will also need to charge more frequently. High mileage drivers need more charging events and fulfill more of these charging needs using fast charging.

	Work - home price (cents/kWh, binned)				
	20 cents less	10 cents less	About same	10 cents more	20 cents more
Work share	0.35	0.31	0.29	0.22	0.18
N	56	103	143	64	29

Table 7: Work charging share as a function of the (binned) difference between work and home charging prices (€ cents/kWh). The data comes from type hw consumers who have charging at both home and work. The first row represents the average share of charging done at work, while the second row represents the number of consumers with the designated price difference bin.

So far, I have focused on how consumers' outside options and annual mileage influence their charging decisions. My data can also show me how responsive consumers are to the relative price difference between different options, which will be very useful in estimating the model. Specifically, type hw consumers - who charge at both home and work - report the (binned) difference between the charging prices they face at work vs. at home. The price difference is reported in five different bins (20 cents less, 10 cents less, about the same, 10 cents more, and 20 cents more). In Table 7, I report the average share of charging done at work conditional on the binned price difference, as well as the number of consumers in each bin. Not surprisingly, the share of charging done at work decreases as the relative price of work charging increases. When work prices are 20 cents less than home, consumers do 35% of charging at work. This decreases to 18% when work prices are 20 cents more than home prices.

In short, this shows that consumers are responsive to charging prices. It also shows how price isn't the only factor determining the choice of charging location: work charging is still utilized when it is significantly more expensive. Also, even when work charging is much cheaper than home, consumers only do 35% of charging at work on average. This suggests that work and home charging are not perfectly substitutable and there are factors other than price influencing where to charge.

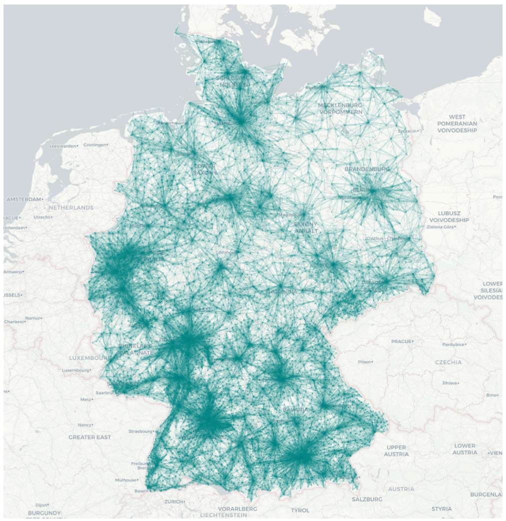
Table 7 also shows how work charging costs tend to be comparable - if not a little cheaper - than home charging costs. Approximately 40 percent of consumers have a work price either 10 or 20 cents lower than the price at home, 36 percent have prices that are about the same, and 24 percent have a work price difference greater than 10 cents. This reflects the fact that commercial electricity rates tend to be lower than residential rates.

In the other dataset (the eMSP Loyalty Benchmarking Survey), I observe aggregated statistics about consumers' preferred EV charging provider as well as the share of consumers who use a paid plan from a given provider. I will use this information to help estimate model. Specifically, I will use the survey-implied paid plan shares to construct moments based on the share of consumers choosing one of a given CPO's paid plans.

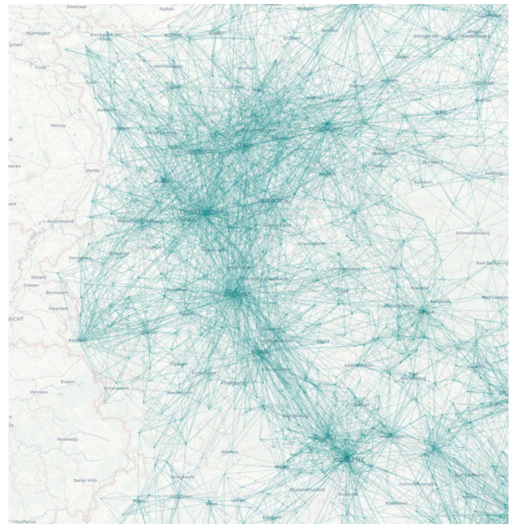
I impose two main restrictions on the survey data I use for sample construction and estimation. First, I exclude Tesla drivers from the sample. This is because Tesla drivers do most of their public charging at the Tesla Supercharger network, which I am not modeling in this paper. As such, it is necessary to drop these drivers from the analysis. Second, I also exclude respondents driving a company car, as my focus is on private consumers. After making these restrictions, I end up with a sample of 1,878 drivers.

2.3 Commuting flow and mobility data

I use data from two German government datasets to understand consumers' driving behavior. For commuting behavior, I use commuting flow data from the German Federal Statistics Office from 2024. The dataset reports the number of individuals who commute between each origin and destination municipality. The data is derived from administrative records for all employees subject to social insurance contributions (akin to FICA taxes in the US), so it represents the vast majority of the working population.



(a) Sampled commuting flows, aggregated by origin and destination code. Commutes of less than 80 km are plotted. Magnitude of flow is omitted for simplicity.



(b) Sampled commuting flows for the Rhine-Ruhr region, aggregated by origin and destination code. Commutes of less than 80 km are plotted. Magnitude of flow is omitted for simplicity.

Figure 4a plots the commuting flows I use in my sample, aggregated by origin and destination municipality code. I subset to commuting flows less than 80 km in length. For simplicity, I don't plot the magnitude of the flow in this figure (i.e. the number of consumers on each path). I also do not trace the actual commuting paths here, but rather use a straight line connecting the two regions. A line exists between cities A and B if consumers commute between those two cities, regardless of how many do. In the model, of course, I do account for the route consumers will take under the assumption that they minimize travel time. The flows are quite granular, giving me a precise sense of the spatial distribution of commuter routes. Additionally, this visualization shows the importance of market definition: there are several distinct clusters of metro areas which have overlapping commuting flows. These represent broad commuting markets and can consist of several major population centers with overlapping commuting flows.

This can be seen more clearly in Figure 4b, which plots the same data for the Rhine-Ruhr metropolitan region and surrounding area (which can be seen as the left-most cluster in 4a, about halfway down). This area has a population of over 10 million and contains many large metro areas (Dortmund, Bochum, Essen, Duisburg, Mönchengladbach, Düsseldorf, Wuppertal, Leverkusen, Cologne, and Bonn). It is clear that many consumers commute to other metro areas within the same region. Consider a charging station located along a highway in this region. Its consumers will be coming from a number of different directions and locations. Consequently, there choice sets (other chargers they consider) will also be different. If I were to specify markets at the city or even metro area level, this would dramatically reduce the number of potential consumers and misrepresent the true set of competing chargers. This motivates me to use a broad market classification, which I detail in subsequent sections.

One critical limitation of this data is that it does not differentiate based on mode of transportation. This means I am unable to see what fraction of commuting trips are by car vs other modes (walking, biking, bus, train, etc.). Furthermore, I cannot directly see how consumers' mode depends on the length of the commute or region they reside in.

Fortunately, the German government conducts periodic country-wide mobility surveys which I use to fill in these gaps. The Mobility in Germany 2023 survey is a large-scale, cross-sectional travel diary survey conducted in 2023 by the German government (BMV 2025). The survey has responses from over 420 thousand individuals comprising over 172 thousand households. Each participating household is assigned a reference date on which they are to record the full set of trips taken for each individual in the household. I observe around 1 million trips in total. For each trip taken by a surveyed individual, the survey contains information such as trip purpose (commuting, leisure, shopping, etc.), length (km), duration (minutes), travel mode (car, bus, train, bike, etc.), city type, and other variables. I cannot see precise spatial data for anonymity reasons. At the household level, I also see the number of vehicles they have available, their average annual mileage (in km), and demographic characteristics.

I use this data in two ways. I first use it to model which commuting trips are taken by car versus other transportation modes. Since the survey reports the mode of transportation used, the trip type, trip distance, and region classification for each trip in the data, I can determine the proportion of work trips in each city type and distance which were taken by car. I then match this with the commuting data to sample *vehicle* commuting trips based on the probability of using a car on the selected trip type.

Furthermore, this data allows me to understand the distribution of non-commuting trips (leisure, shopping, etc.), which I will use to simulate consumers' non-commuting trips in the model. I detail this procedure in the section which discusses my sample construction.

2.4 OpenStreetMap

I use data from OpenStreetMap (OSM), an open-source mapping project which freely offers comprehensive information on road networks, amenities, and points of interest (OpenStreetMap contributors 2024). I use this data in a number of ways. First, consistent with the commuting and mobility data, I simulate a large number of driving routes. For each route, I find all chargers within 5 km and find the detour time needed to access the charger, allowing consumers to re-optimize their route. This allows me to construct consumers' choice sets and the relative convenience of accessing a particular charger for them. Further details are included in the estimation methodology section.

Secondly, I use the OSM data to find all amenities and points of interest proximate to each charging station. The availability of services (food, restrooms, coffee, etc.) nearby a charging station may play an important role in the charging choice. I also determine whether the charging station is located at an Autobahn service area. Service areas are located directly on the Autobahn and often provide amenities such as fuel, restaurants, cafes, and restrooms. Further details of all the variables I construct using the OSM data are included in the estimation methodology section.

2.5 Vehicle registration

The spatial nature of my model of consumer charging demand requires that I know the spatial distribution of electric vehicles. To address this need, I utilize vehicle registration data from the German Federal Motor Transport Authority (Kraftfahrt-Bundesamt), commonly abbreviated as KBA. The agency publishes a variety of statistics regarding the existing vehicle fleet as well as new vehicle registrations. There are two primary reports that I employ for my analysis.

First, I use the KBA's FZ 27 dataset, which reports the stock of electric vehicles within each zipcode on a quarterly basis. This dataset includes every vehicle on the road, not just newly-registered vehicles. This allows me to model the spatial distribution of EV drivers at a very granular level.

In addition, I use the FZ 6 dataset, which reports the aggregate stock of each make, model, and trim level on an annual basis. This data is aggregated to the country level and therefore does not give information on local market shares of each vehicle. I make the necessary assumption that national vehicle market shares are representative of local shares. I match this dataset with information on each EV model's battery size, effective range, and maximum charging speed scraped from chargeprice.com. The main purpose of this data is to understand the overall distribution of vehicle characteristics (range, charging speed), which I will use to simulate consumer types. A histogram of these charging speeds (based on vehicle market share) is included in Figure 5. The significant heterogeneity in charging speeds is notable. Details about how consumer vehicle characteristics are drawn can be found in the estimation methodology section.

3 Model

I model both the demand and supply side of the market for EV fast charging. On the demand side, consumers choose where to charge based on their driving patterns, available charging options, and vehicle characteristics. I assume a nested BLP-style demand model which incorporates rich consumer heterogeneity. Additionally, consumers may elect to purchase a monthly subscription from a CPO which lowers their charging costs within the CPO's net-

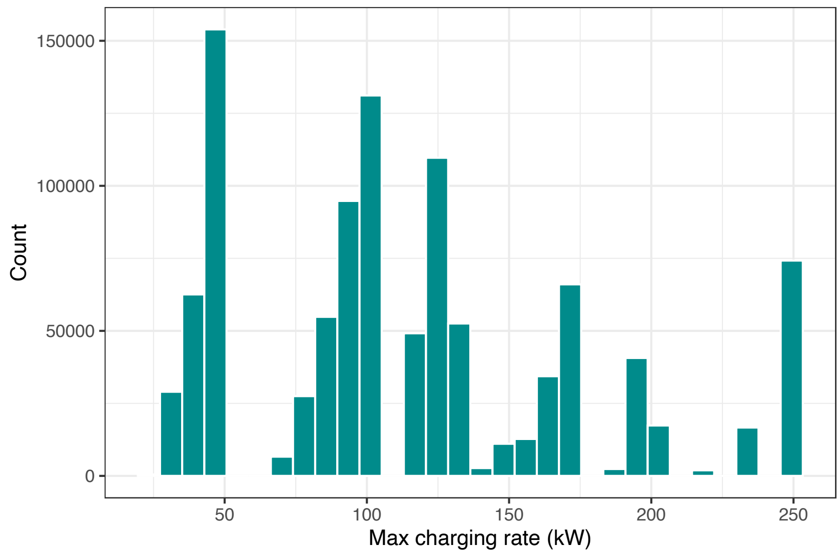


Figure 5: Distribution of EV maximum charging rate as of September 2024 based on registration statistics

work. On the supply side, CPOs set charging prices and (if applicable) plan fees to maximize profits under the assumption of Bertrand-Nash competition.

3.1 Consumers

I model consumers' demand for both public and private charging using a nested logit framework with individual heterogeneity in the style of BLP. Each consumer first chooses whether to subscribe to any of the monthly plans offered by CPOs. These plans reduce the cost of charging at the CPO in exchange for a monthly fee. The utility from each plan depends on the inclusive value of charging conditional on picking that plan as well as the plan fee. The inclusive value of charging is derived from a nested logit model of consumer charging. In this model, consumers take a variety of trips which require a certain amount of charging. Consumers then choose where to charge on each charging event to maximize their utility. They choose between slow charging outside options (home, work, and public slow charging) or public fast charging (the inside good). Their choice set of public fast chargers is determined by the set of chargers adjacent to each route.

The number of required charging events is denoted by Q_i. Q_i is determined based on the total kWh used across their routes, depending on route length and their vehicle's efficiency (kWh/km). Specifically, letting D_i indicate electricity used and B_i denote battery size, the total number of (normalized) charging events is given by $Q_i = \frac{D_i}{0.6B_i}$. 0.6 is included in the denominator to reflect the average amount of the battery charged in a fast charging session.

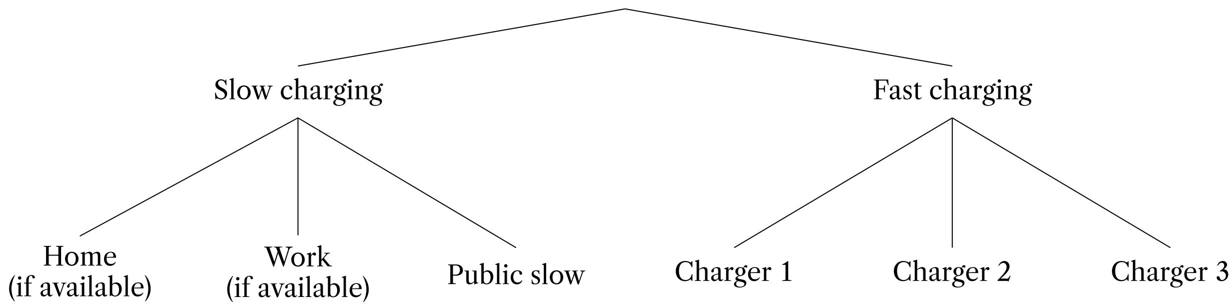


Figure 6: Nesting structure of demand conditional on plan choice

I assume each charging event replenishes 60% of the consumer's battery, corresponding to charging from 20-80% of battery capacity. This is necessary since consumers rarely fully charge at public fast chargers, instead preferring to charge until 80% since charging speed slows significantly as the battery fills up.

This normalization ensures that utility levels are comparable across different charging types (home, work, etc.). This does not affect the amount of electricity charged at each option - if they do four home charging events, each charging 30% of the battery, it's equivalent to doing two charging events of 60%. I care only about the electricity share at each option type rather than the particular number and size of the charging events.

The consumer chooses where to do each of their Q_i charging events to maximize their utility. Consumers can choose to charge at public fast chargers along the route, public slow chargers, home (if available), or at work (if available). I use a nested structure to model consumers' choice between these heterogeneous options.

The nesting structure of consumers' options is represented in Figure 6. The first branch represents the different slow charging options a consumer may have. The set of available options (home, work, and public slow charging) will differ by consumer. The second branch represents the consumer's choice of fast chargers. I assume that the consumer chooses which route to charge on, then chooses the optimal charger along the selected route. This allows for different substitution patterns between chargers along the same route vs. ones on different routes.

In short, the consumer's choice problem takes the following sequence:

1. Consumer picks plan to maximize expected utility from charging

2. Conditional on plan membership, for each required charging event, consumer decides on charging type (slow or fast)

    - If slow:

        (a) Home, work, or public slow charging (depending on availability)

    - If fast:

(a) Which charger to charge at

I summarize the nonlinear demand parameters in my model into the vector θ:

$$\theta = (\alpha, \alpha_{plan}, \alpha_{mileage}, \beta_{detour}, \beta_{speed}, \sigma_{trip}, \sigma_{loc}, \sigma_{priv}, \sigma_{speed}, \sigma_{paid}, v_h, v_w, v_s)$$

I will discuss each parameter as they are introduced. There are additional linear parameters that are estimated during the demand estimation procedure.

I felt it most natural to walk through the consumer's utility maximization problem in reverse order, starting with their utility from each charging event. I then work my way backwards through the route and charging type choice. I conclude by discussing consumers' plan choice.

Fast charging: I begin with the choice of charger conditional on taking a given route.

Consumers are characterized by their set of driving routes R_i as well as a type vector $\omega_i = (\lambda_i, \kappa_i, q_i, Q_i, p_{ih}, p_{iw})$. $\lambda_i \in \{hw, h, w, n\}$ represents the type of outside options that are available to the consumer. κ_i refers to the maximum charging speed (kW) of consumer i's vehicle. Letting B_i denote the size of their vehicle's battery, $q_i = 0.6B_i$ represents consumer i's charging demand (in kWh) per public charging event under the assumption that consumers charge from 20-80%. Finally, Q_i reflects the number of charging events (of size q_i) needed to fulfill the drivers' charging needs from the routes they take. p_{ih} and p_{iw} refer to the home and work charging prices that the consumer faces (if available). These are simulated based on the empirical distribution in the data. More details are included in the estimation methodology section.

The price that a consumer pays for public fast charging depends on their choice of charging subscription (if any) and the network of the station they are charging at. Each consumer chooses a plan n from a set of plans $N = \{0, 1, \ldots, N_p\}$. $n = 0$ can be understood as a compound option where the consumer does not subscribe to any particular plan. Instead, the consumer pays each CPO's basic per-kWh price whenever they charge at any of their stations. If, conversely, a consumer selects a plan n from CPO A, they will receive a discount when charging at stations of A and pay other CPOs' basic price when charging at other CPOs. To fix ideas, a $n = 0$ consumer would pay €0.59/kWh at EnBW and €0.69 at Ionity. A subscriber to EnBW would pay €0.49 at EnBW and €0.69 at Ionity. Conversely, an Ionity subscriber pays €0.59 at EnBW and €0.49 at Ionity. I assume that consumers can only pick one paid plan.

Consider the case of consumer i who has selected plan n and has chosen to charge at a fast charger along route r. Let (O, D) refer to the origin and destination points associated with route r. Let the consumer's choice set along route r be denoted by $C(r)$ and represent the set of public fast chargers within 5 kilometers of the optimal route between O and D. Given nonlinear parameter vector θ, consumer i with plan n and type ω_i receives the following

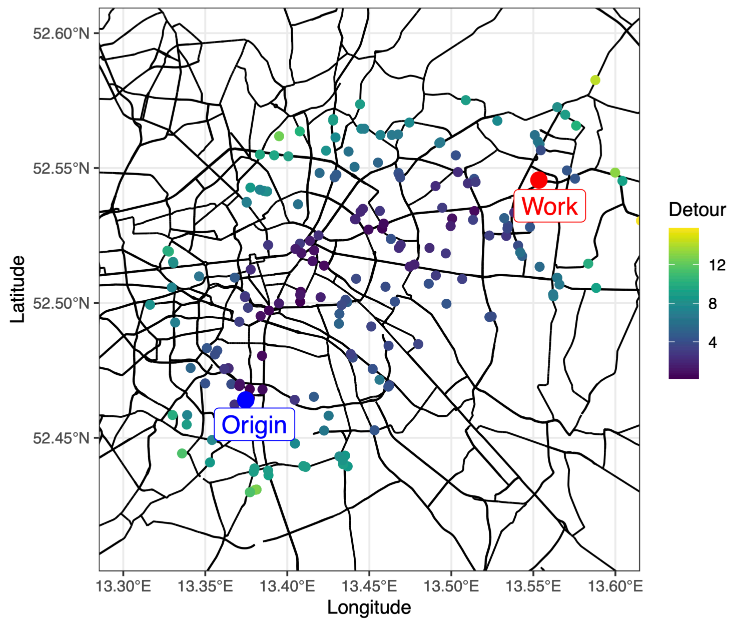


Figure 7: Example of the choice set associated with a consumer's commute. The color of each dot indicates the detour time (relative to the original route) in minutes. Only major roads (i.e. Autobahn and primary highways) are plotted for clarity.

utility from charging at station $j \in C(r)$:

$$u_{ijt}(p_j(n), \theta, \omega_i) = \underbrace{\beta X_j}_{\delta_j} + \underbrace{\beta_{detour}\tau(j,r) - \alpha p_j(n) + \beta_{speed}\min\{\kappa_i, X_j^s\}}_{\mu_{ijt}}$$
$$+ \xi_j + \underbrace{\zeta_{in}^{plan} + (1-\sigma_{paid})\zeta_{in}^{paid} + (1-\sigma_{speed})\zeta_{ic}^{fast} + (1-\sigma_{loc})\varepsilon_{ij}}_{\text{Nested logit shocks}}$$

In this equation, X_j represents the (non-speed) characteristics of station j. This contains the number of chargers in each kW speed bin ($\{(0,22], (22,50], (50,150], (150,250], (250,500]\}$) as well as indicator variables reflecting the major road types near the charger (Autobahn, highway, trunk primary) as well as the presence of nearby amenities (Autobahn service area, fast food, restaurant, convenience store, grocery store, etc.). I also include a network fixed effect.

In the individual-specific component μ_{ijt}, $\tau(j,r)$ represents the detour time associated with accessing $j \in C(r)$. Define $d(l_0, l_1)$ as the time it takes to drive between arbitrary point l_0 and l_1 assuming the driver takes the route which minimizes travel time. Then, the detour time $\tau(j,r)$ takes this form:

$$\tau(j,r) = d(O,j) + d(j,D) - d(O,D)$$

That is, $\tau(j,r)$ is the time it takes to travel from the origin O to the charger j to the destination O, minus the original travel time. Figure 7 provides an example of the choice set and associated detour times for a given commuting route. This specification allows consumers to re-optimize their route based on the location of the charger. The 5 km cutoff of $C(r)$ gives consumers ample flexibility to pick better chargers and re-optimize their route while also placing sensible restrictions on the size of their choice set.

The coefficient α represents consumers' price sensitivity. This is assumed to be common across individuals, rather than a random coefficient. I capture consumers' preferences for charging speed using β_{speed}. The realized speed of charging given the consumers' maximum charging speed (κ_i) and the station's maximum charging speed (X_j^s) is $\min\{\kappa_i, X_j^s\}$. Intuitively, the speed of charging is determined by the slowest of the two sides: either the charger or the vehicle. This introduces natural heterogeneity in preferences for charging speed. Consumers with slower-charging vehicles experience little speed differences across networks, while fast-charging vehicles experience more speed differences.

I assume that ε_{ij}, ζ_i^{fast}, ζ_{in}^{paid}, and ζ_{in}^{plan} are IID Type I Extreme Value random variables. σ_{loc} represents the correlation in the utility shocks between public fast chargers. σ_{speed} represents the correlation in utility shocks for the choice between the inside option (fast charging) and the outside option nest (slow charging). Finally, σ_{paid} represents the correlation in utility shocks within the paid plan nest.

Assuming that the consumer with plan n chooses to charge along route r, the probability of charging at station j is given by

$$s_{j|F}(p(n), \theta, \omega_i) = \frac{\exp(u_{ij}(p_j(n), \theta, \omega_i)/(1-\sigma_{loc}))}{\sum_{k \in C(r)} \exp(u_{ik}(p_k(n), \theta, \omega_i)/(1-\sigma_{loc}))}$$

Similarly, the inclusive value of fast charging is expressed as the following:

$$V_F(p(n), \theta, \omega_i) = (1-\sigma_{loc}) \log \left[\sum_{k \in C(r)} \exp[(\delta_k + \mu_{ik}(p_k(n), \omega_i) + \xi_k)/(1-\sigma_{loc})] \right]$$

I now discuss the utility consumers get from the outside options: home, work, and public slow charging. I assume that consumers charge the same amount per charging event - q_i - as during fast charging events. This is a normalization to ensure that each option is comparing equivalent amounts of charging.

The utility from home charging is described by the following:

$$u_{ih}(\theta, \omega_i) = \begin{cases} v_h - \alpha p_{ih} + \zeta_{in}^{plan} + (1-\sigma_{paid})\zeta_{in}^{paid} + (1-\sigma_{speed})\zeta_i^{slow} + (1-\sigma_{priv})\varepsilon_{ih} & \text{if type} \in \{h, hw\} \\ -\infty & \text{if type} \in \{w, n\} \end{cases}$$

where v_h represents consumers' mean utility from charging at home. This is assumed to be common across all home charging consumers. p_{ih} refers to the price per kWh consumer i pays for home charging. This is heterogeneous across individuals, reflecting the fact that consumers differ in their home charging costs. When simulating consumers, I will draw a home charging price for each consumer. Details about the simulation of home charging prices can be found in the data construction section. Types w and n cannot charge at home and incur infinite disutility from choosing this option. As before, ζ_{in}^{plan}, ζ_{in}^{paid}, ζ_{i}^{slow}, and ε_{ih} are IID Type I Extreme Value random variables. σ_{priv} represents the correlation in utility shocks for slow charging options.

Similarly, the utility for work charging takes the following form:

$$u_{iwt}(\theta,\omega_i) = \begin{cases} v_w - \alpha p_{iw} + \zeta_{in}^{plan} + (1-\sigma_{paid})\zeta_{in}^{paid} + (1-\sigma_{speed})\zeta_{i}^{slow} + (1-\sigma_{priv})\varepsilon_{iw} & \text{if } \lambda_i \in \{w, hw\} \\ -\infty & \text{if } \lambda_i \in \{h, n\} \end{cases}$$

where v_w represents consumers' mean utility from charging at work. p_{iw} denotes consumer i's work charging price per kWh. Similar to home charging costs, this is heterogeneous across individuals. I discuss how work charging prices are simulated in the data construction section. As before, types h and n cannot charge at work and incur infinite disutility from choosing this option.

Finally, consumers' utility from slow charging is given by the following:

$$u_{iSt}(\omega_i) = v_s - \alpha p_s + \zeta_{in}^{plan} + (1-\sigma_{paid})\zeta_{in}^{paid} + (1-\sigma_{speed})\zeta_{i}^{slow} + (1-\sigma_{priv})\varepsilon_{is}$$

v_s refers to consumers' mean utility from using slow charging. I assume that the cost of slow charging is €0.50/kWh based on publicly available statistics. I abstract away from modeling the choice of slow charging station as I do not have data on slow charging demand. Finally, I assume that all consumers have access to slow charging.

The inclusive value of choosing the slow charging nest can be expressed as:

$$V_S(\theta,\omega_i) = \begin{cases} (1-\sigma_{priv})\log(\exp(\frac{v_h-\alpha p_{ih}}{1-\sigma_{priv}}) + \exp(\frac{v_w-\alpha p_{iw})}{1-\sigma_{priv}}) + \exp(\frac{v_s-\alpha p_s}{1-\sigma_{priv}})) & \text{if } \lambda_i = hw \\ (1-\sigma_{priv})\log(\exp(\frac{v_h-\alpha p_{ih}}{1-\sigma_{priv}}) + \exp(\frac{v_s-\alpha p_s}{1-\sigma_{priv}})) & \text{if } \lambda_i = h \\ (1-\sigma_{priv})\log(\exp(\frac{v_w-\alpha p_{iw}}{1-\sigma_{priv}})) + \exp(\frac{v_s-\alpha p_s}{1-\sigma_{priv}})) & \text{if } \lambda_i = w \\ v_s - \alpha p_s & \text{if } \lambda_i = n \end{cases}$$

Charging type choice: Conditional on choosing to charge, consumers must choose between the slow charging and fast charging nests. Their probability of charging in the fast and slow charging nests takes the following forms:

$$s_{F|c}(p(n),\theta,\omega_i) = \frac{\exp(V_F(p(n),\theta,\omega_i)/(1-\sigma_{speed})}{\exp(V_S(\theta,\omega_i)/(1-\sigma_{speed})) + \exp(V_F(p(n),\theta,\omega_i)/(1-\sigma_{speed}))}$$

$$s_{S|c}(p(n),\theta,\omega_i) = \frac{\exp(V_S(\theta,\omega_i)/(1-\sigma_{speed}))}{\exp(V_S(\theta,\omega_i)/(1-\sigma_{speed})) + \exp(V_F(p(n),\theta,\omega_i)/(1-\sigma_{speed}))}$$

Additionally, the inclusive value of each charging event can be expressed as the following:

$$V_c(p(n), \theta, \omega_i) = (1 - \sigma_{speed}) \log(\exp(V_S(\theta, \omega_i)/(1 - \sigma_{speed})) + \exp(V_F(p(n), \theta, \omega_i)/(1 - \sigma_{speed})))$$

Plan choice: Given the expected utility from each plan, consumers choose whether to subscribe to any of the available plans. Given Q_i total charging events, the consumers' expected utility from selecting a given plan n can be expressed as:

$$V_n(p(n), \theta, \omega_i) = Q_i V_c(p(n), \theta, \omega_i) - \alpha^i_{plan} \varphi_n + (1 - \sigma_{paid}) \zeta^{paid}_{in} + \zeta^{plan}_{in}$$

Intuitively, the plan's value is the inclusive value for each charging event times the number of times the consumer expects to charge, minus the disutility from the plan fee φ_n (if applicable). α^i_{plan} reflects the consumers' sensitivity to plan fees. I parameterize α^i_{plan} to be a function of mileage, where $\alpha^i_{plan} = \alpha^0_{plan} + \alpha^{mileage}_{plan}\text{mileage}_i$. This allows consumers with higher mileage to differ in their sensitivity to plan fees relative to low mileage consumers. Finally, if $n = 0$ (corresponding to the consumer not selecting any subscription), $p(n)$ is just the vector of basic prices for each CPO and $\varphi_0 = 0$.

I assume that consumers first pick whether to subscribe to a paid plan, or whether to choose the outside option of no subscription ($n = 0$). Conditional on picking a paid plan, the probability of picking plan n is given by

$$s_{n|Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = \frac{\exp(V_n(p(n), \theta, \omega_i)/(1 - \sigma_{paid}))}{\sum_{n'>0}^{N_{plan}} \exp(V_{n'}(p(n'), \theta, \omega_i)/(1 - \sigma_{paid}))}$$

The inclusive value of a paid plan is

$$V_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = (1 - \sigma_{paid}) \log(\sum_{n'>0} \exp(V_{n'}(p(n'), \theta, \omega_i)))$$

The probability a consumer picks a paid plan is given by

$$s_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = \frac{\exp(V_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i))}{\exp(V_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)) + exp(V_0(p(0), \theta, \omega_i))}$$

where V_0 denotes the utility of the outside option (no subscription).

The probability of picking a particular paid plan n is thus

$$s_n(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = s_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) \times s_{n|Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)$$

The probability of choosing not to subscribe to any plan is given by

$$s_0(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = \frac{exp(V_0(p(0), \theta, \omega_i))}{\exp(V_{Paid}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)) + exp(V_0(p(0), \theta, \omega_i))}$$

Aggregate demand: The demand for station j from consumer i with plan n, routes R_i, and type ω_i is given by the following:

$$q_{ijn}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i) = Q_i \times \underbrace{s_n(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)}_{\text{Plan choice}} \times \underbrace{s_{F|c}(p(n), \theta, \omega_i)}_{\text{Fast charging}} \times \underbrace{s_{j|F}(p(n), \theta, \omega_i)}_{\text{Choosing station } j}$$

I use this to construct the aggregate demand for stations of network m from plan n:

$$D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n) = \sum_{j \in J(m)} \sum_{i \in I} q_{ijn}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)$$

where $J(m)$ denotes the set of stations in network m.

I also define market shares for use in demand estimation:

$$s_j(\boldsymbol{p}, \boldsymbol{\varphi}, \theta) = \frac{\sum_{i \in I} \sum_{n=0}^{N_{plan}} q_{ijn}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)}{\sum_{i \in I} Q_i}$$

Finally, I define $\Lambda_n(\boldsymbol{p}, \boldsymbol{\varphi}, \theta)$ as the mass of drivers on plan n:

$$\Lambda_n(\boldsymbol{p}, \boldsymbol{\varphi}, \theta) = \sum_{i \in I} s_n(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, \omega_i)$$

3.2 Supply side

I now present the supply side of my model. I assume that networks choose prices and plan details (if applicable) in order to maximize profits from charging in the given period. I assume networks set network-wide prices. All networks must pay a 19% Value Added Tax (VAT), which applies both to the charging price as well as any subscription revenues. Furthermore, I assume Bertrand-Nash competition. I do not model entry or exit of stations. Additionally, while networks have fixed costs and various costs from maintenance, I do not model these since they should not affect static profit maximization in a given period.

Consider first a CPO m which does not offer any paid plans. I assume that marginal costs (before VAT) are identical throughout the network and are equal to c_m. I discuss this assumption later in this section. Network m's profits can be expressed as the following:

$$\Pi_m(\boldsymbol{p}, \boldsymbol{\varphi}) = (p_m/1.19 - c_m) \sum_{n=0}^{N_{plans}} D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)$$

Network m has only one choice variable: the basic price available to all consumers (p_m). By changing p_m, networks are controlling the price that all consumers pay to access their network (regardless of plan). Nevertheless, consumers subscribing to paid plans from other providers will have heterogeneous responses since the the vectors of other prices they face are specific to their plan.

The first order condition for p_m is given by the following:

$$0 = (p_m/1.19 - c_m) \sum_{n=0}^{N_{plans}} \frac{\partial D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\partial p_m} + 1/1.19 \sum_{n=0}^{N_{plans}} D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)$$
$$\iff p_m = 1.19 \cdot c_m - \frac{\sum_{n=0}^{N_{plans}} D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\sum_{n=0}^{N_{plans}} \frac{\partial D_m(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\partial p_m}}$$

This yields the standard Bertrand-Nash markup formula.

The maximization problem is more complex for CPOs that offer plans. Instead of just setting one basic price, these CPOs set 1) a basic price, 2) charging prices for each plan, and 3) monthly subscription fees for each plan. I present the equations which characterize joint optimality of these three decision variables. For simplicity, consider a CPO A which offers one paid plan. Let n_A denote the index of A's paid plan. Consumers on a plan $n \neq n_A$ pay the basic price p_A^{Basic} per kWh. Consumers on plan n_A will pay p_A^{Paid} per kWh and monthly fee φ_A.

$$\Pi_A(\boldsymbol{p}, \boldsymbol{\varphi}) = \underbrace{(p_A^{\text{Basic}}/1.19 - c_A) \sum_{n \neq n_A} D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}_{\text{Profit contribution from basic charging}} + \underbrace{(p_A^{\text{Paid}}/1.19 - c_A) D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n_A)}_{\text{Profit contribution from paid plan } n_A} + \frac{1}{1.19} \underbrace{\Lambda_{n_A}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta) \varphi_A}_{\text{Plan fee revenue}}$$

There are three first order conditions: p_A^{Basic}, p_A^{Paid}, and φ_A.

$$[p_A^{\text{Basic}}] \quad 0 = (p_A^{\text{Basic}}/1.19 - c_A) \sum_{n \neq n_A} \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\partial p_A^{\text{Basic}}} + \frac{1}{1.19} \sum_{n \neq n_A} D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n) + (p_A^{\text{Paid}}/1.19 - c_A) \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n_A)}{\partial p_A^{\text{Basic}}} + \frac{1}{1.19} \frac{\partial \Lambda_{n_A}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta)}{\partial p_A^{\text{Basic}}} \varphi_A$$
$$[p_A^{\text{Paid}}] \quad 0 = (p_A^{\text{Basic}}/1.19 - c_A) \sum_{n \neq n_A} \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\partial p_A^{\text{Paid}}} + (p_A^{\text{Paid}}/1.19 - c_A) \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n_A)}{\partial p_A^{\text{Paid}}} + \frac{1}{1.19} D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n_A) + \frac{1}{1.19} \frac{\partial \Lambda_{n_A}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta)}{\partial p_A^{\text{Paid}}} \varphi_A$$
$$[\varphi_A] \quad 0 = (p_A^{\text{Basic}}/1.19 - c_A) \sum_{n \neq n_A} \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n)}{\partial \varphi_A} + (p_A^{\text{Paid}}/1.19 - c_A) \frac{\partial D_A(\boldsymbol{p}, \boldsymbol{\varphi}, \theta, n_A)}{\partial \varphi_A} + \frac{1}{1.19} \frac{\partial \Lambda_{n_A}(\boldsymbol{p}, \boldsymbol{\varphi}, \theta)}{\partial \varphi_A} \varphi_A + \frac{1}{1.19} \Lambda_{n_A}(\boldsymbol{p}, \varphi, \theta)$$

The main insight here is the fact that the CPO internalizes the effect of each variable. For instance, consider what happens if the firm increases p_A^{Basic}. This has two effects: the direct effect is that consumers who don't have A's paid plan will reduce their charging demand for network A. However, following the increase in the basic price, some consumers will choose to subscribe to A's paid plan. Similarly, increasing p_A^{Paid} will decrease demand from n_A plan users and cause substitution to other plans. However, since A gets a higher margin from consumers accessing their network from other plans, they can potentially recapture a portion of lost profits. These additional considerations set these CPOs apart from CPOs which only offer basic plans.

I now discuss how I model marginal cost within this framework. I assume the marginal cost is comprised of two components: the price of electricity and a fixed amount per kWh in GHG quota revenue. I furthermore assume that the price of electricity is common across all stations within a given network. This is not an unrealistic assumption given Germany's integrated electricity market. Since it is one large grid, CPOs can source power for their entire network of stations in aggregate as opposed to having separate contracts with each local utility.

I use publicly available statistics on commercial electricity contracts reported by the German government to infer CPOs marginal costs.[6] In Germany, the electricity rate available to commercial consumers is decreasing in the entity's annual electricity usage. Users with the smallest usage pay the highest prices, whereas those with the highest usage pay the lowest prices. The price is generally determined by determining which usage bin a consumer falls into: for example, 0 to 20 MW, 20 to 500 MW, 500 to 2,000 MW, etc. The full price schedule and further details can be found in 14 in the appendix.

I assume that non-utility CPOs pay a commercial electricity rate corresponding to their total (inferred) level of network demand. I aggregate each CPO's demand (assuming an average charge event size of 35kWh) and find the corresponding electricity price based on Table 14. Utility-backed CPOs will have different costs in the sense that they are buying power directly from the wholesale market and supplying it to themselves. This eliminates the markup included in commercial electricity contracts. I assume that their cost of electricity is the wholesale price plus all applicable grid fees, taxes, and levies for the electricity. The effective price paid by a networks includes mandatory taxes and fees but excluding VAT, as networks are eligible for remittance of VAT paid when obtaining electricity.

Finally, I also assume that CPOs earn €0.04/kWh through the sale of GHG quota credits. The German government's Greenhouse Gas (GHG) quota requires that fuel distributors either 1) reduce emissions by a set amount per year or 2) purchase credits in order to meet their reduction quota. Credits are given to EV owners and public charging infrastructure based on their emissions reduction. That is, for each kWh sold by a CPO, they receive a certain amount of credits based on the estimated amount of emissions averted. This depends on the overall energy mix in the grid. CPOs can gain a small amount of revenue by selling their credits to fuel distributors that are not capable of meeting their quota. While the value of these credits fluctuates over time due to quota targets and the grid mix, their value averaged around €0.04/kWh sold during the sample period.[7]) I use this value in my analysis and assume that CPOs marginal costs are €0.04/kWh lower than the cost of electricity they use.

[6]https://www-genesis.destatis.de/datenbank/online/url/3d80e83e

[7]https://emobilitaet.online/news/experteninterviews/8451-interview-thg-quote-2026-preise

4 Estimation methodology

4.1 Simulating consumer types

Spatial distribution of consumers: I use the KBA vehicle registration data to sample EV drivers. Specifically, using the KBA's FZ 27 dataset, I observe the stock of electric vehicles in each zipcode. I construct 20 representative consumers in each zipcode. If there are N drivers in the zipcode, each simulated driver is given a weight of $\frac{N}{20}$.

Route and choice set construction: I now outline my process for sampling commuting routes. For a given origin region, I use the commuting flow data to determine the probability that a consumer commutes to each destination region. I repeat this for all origin and destination combinations with a commuting distance less than 100 km to obtain the full distribution of commuting paths.

Since the commuting data does not differentiate by mode of travel, I use the Mobility in Germany data to determine the probability of a given commuting trip being by car, conditional on the trip distance and origin region type. I model this using a logit regression with distance as a covariate. I assume both the intercept and distance coefficient are a function of distance.

$$P(car \mid dist, region = r) = \frac{\exp(\beta_0^r + \beta_1^r \text{dist})}{1 + (\exp(\beta_0^r + \beta_1^r \text{dist})}$$

The resulting probabilities are plotted in Figure 14 in the appendix. The results are as one may expect: the probability of commuting via car is increasing in trip distance and decreasing in urbanization. Based on these estimates, I then back out the probability each commuting trip was taken via car using Bayes' rule. After taking this into account, I can then sample routes from the (inferred) distribution of car commuting trips.

For each sampled consumer, I sample a commuting path from the distribution of car commuting trips originating in the region. This relies on the assumption that commuting behavior is homogeneous across zipcodes within a municipality. This is a necessary assumption since I do not have finer commuting flow data. Each commuting path is assumed to begin at the centroid of the zipcode. The destination location is sampled in a sequential manner. First, the destination municipality is sampled according to the distribution of vehicle commuting trips. Then, within a destination municipality, I sample the destination according to the empirical distribution of workplaces obtained from the OSM data.

Non-commuting trips are sampled in a similar way. First, I use the Mobility in Germany data to find the distribution of non-commute trip distance conditional on using a car as the mode of transportation. I condition this on the drivers' region type. I discretize this distribution into 5 km bins. In order to simulate non-commuting routes, I first sample a distance bin (e.g., 15 to 20 km). I then sample the destination point based on the distribution of business establishments and points of interest within this distance band (again sourced from the OSM data).

For each sampled trip, I find the route through the road network which minimizes the time to reach the destination. To do this, I utilize the `osmnx` Python package (Boeing 2025), which uses Dijkstra's algorithm and accounts for the driving speed on different road types. As a necessary simplification, I assume traffic is negligible. I then find all charging stations within 5 km of the resulting route. I define this as the consumers' choice set. For each charger within the choice set, I compute the travel time for both 1) the trip from the origin to the charger and 2) the trip from the charger to the destination. These are again found using Dijkstra's algorithm. This allows drivers to re-optimize their path (without having to return to the original path). The detour time is computed as the difference between the total travel time associated with accessing the charger and the original travel time (driving directly to the destination). An example of this can be found in 7.

Each of the sampled consumers in each zipcode is assigned one commuting route and four non-commuting routes. I assume they take the commuting route every weekday and take each non-commuting route once a week. I then compute the mileage implied by these trips, which will be used to determine the number of charging events they need.

For all chargers which appear in at least one choice set, I compute the minimum detour required to access each charger across all of the driver's routes. That is, if a given charger requires a seven minute detour on trip A but only a three minute detour on trip B, I use a detour time of three minutes when computing consumer's utility from charging at that station. This simplification prevents me from having to model both the choice of which route to charge on as well as which charger along that route to select. As I lack the highly granular data that would allow me to model route choice, this simplification is necessary.

Vehicle characteristics: I assign vehicles to simulated consumers based on the observed market shares of each vehicle (in the existing vehicle fleet). However, I need to be more careful than randomly assigning vehicles to consumers independent of their driving behavior. Drivers' choice of EV is endogenous and is likely correlated with their driving behavior. Consumers with longer commutes may pick a longer range EV, and those who barely drive will find long range superfluous. Or, in the other direction, longer range EVs may cause people to choose longer commutes. Regardless, there is potential correlation here that must be addressed.

In fact, I do find evidence suggesting this correlation is important. In the USCALE driver survey data, I observe both the (binned into 100 km intervals) range of the driver's EV as well as their annual mileage (binned into 5,000 km intervals). Figure 15 in the appendix illustrates the share of survey respondents within each annual mileage bin who select an EV in the specified range bin. Range is indeed correlated with mileage: high mileage drivers are more likely to have long range vehicles than low mileage drivers.

To simulate consumers' choice of EV while preserving this correlation structure, I first use their (simulated) annual mileage together with the survey data to determine the probability they pick each range bin. After picking a range bin, I then randomly draw an EV from within the selected range bin with probability proportional to its market share within that range segment.

Consequently, each consumer is now assigned an EV with corresponding range, battery size, charging speed, and other vehicle characteristics used within the model. Now that I know their EV's range, I can construct the number of charging events needed to fulfill the charging needs implied by their (simulated) mileage. This is obtained simply by taking the incurred mileage and multiplying by their EV's average efficiency (in terms of kWh/km), after which I divide by 0.6 times the size of the battery (corresponding to a charge from 20-80%). This yields the number of (normalized) charging events required by their driving behavior.

Home and work charging: A key component of my model is the set of alternative charging options available to the consumer. I simulate these as a function of consumers' region type according to the probabilities in Tables 3a and 3b. I currently assume that home charging availability is independent of work charging availability conditional on the type of city the consumer resides in. This allows me to sample home and work charging independently of each other.

Home and work charging prices: I simulate the charging prices consumers face at home and the workplace (if available) through a bit of fancy statistical footwork.

To understand the distribution of home charging prices, I use data from a large-scale German home charging survey conducted in 2022. This survey involved households who had received a subsidy for the installation of home charging equipment. It asks them about many aspects of their charging experience, but the most important for my purposes is that it asks consumers to report the price per kWh they pay to charge at home. Further details can be found in the appendix.

This survey was conducted in 2022, while my sample is in September of 2024. This means that the average home charging price in the survey (€0.31/kWh) will not accurately reflect the prices consumers face in September 2024. I assume that the mean charging price for consumers in my sample is equal to the mean German household electricity price in the second half of 2024 (€0.39/kWh)[8]. As a necessary assumption, I assume that the standard deviation of prices is the same between both periods. After winsorizing the data, I estimate a standard deviation of €0.052/kWh. I then simulate home charging prices under the assumption they follow a Normal distribution with $p_h \sim N(\mu_h, \sigma_h^2)$, where $\mu_h =$ €0.394/kWh and $\sigma_h =$€0.052/kWh.

It now remains to simulate work charging prices. I do not observe work charging prices directly, but I do observe summary statistics about the difference between work and home charging prices in the USCALE driver survey. Specifically, survey respondents who have charging at both home and work report the (binned) difference between work and home charging prices (20 cents less, 10 cents less, about the same, 10 cents more, 20 cents more).

I model work charging prices as normally distributed $p_w \sim N(\mu_w, \sigma_w^2)$, where μ_w and σ_w^2

[8]https://ec.europa.eu/eurostat/databrowser/bookmark/5e77ac1a-5efe-46fb-9471-8bd504bdf6f2?lang=en

are to be estimated. I estimate these using GMM. Specifically, given that home prices are distributed $p_h \sim N(\mu_h, \sigma_h^2)$ and work prices are distributed $p_w \sim N(\mu_w, \sigma_w^2)$ (and assuming independence of home and work prices[9]), their difference is distributed $p_w - p_h \sim N(\mu_w - \mu_h, \sigma_w^2 + \sigma_h^2)$. I create a set of bins corresponding to each bin in the USCALE driver survey (for example, 10 cents less in the sample corresponds to a price difference ranging from -15 to -5 cents, assuming consumers' responses are rounded to the nearest bin). I form one moment for each bin, comparing the implied probability of price differences within each bin to the observed proportion of consumers with that price difference. I then stack these five moments to form the GMM objective function.

I estimate that $p_w \sim N(\mu_w, \sigma_w^2)$ with μ_w= €0.368/kWh and σ_w =€0.098/kWh. The lower average cost and higher dispersion are not necessarily surprising. Commercial electricity prices tend to be lower than household prices, which explains the level shift. Additionally, some employers may subsidize work charging for their employees, which would also lower the average cost. The higher variance can be rationalized by the fact that commercial electricity prices are decreasing in annual usage, meaning that heterogeneity in employer size could play a role in the dispersion of work charging prices.

4.2 Charging station characteristics

I use the scraped charger data in addition to the OSM data to construct the charger characteristics I use in estimation. From the charger data, I observe key variables such as the charger's network, number of chargers, and speed of each charger within the station. I use these to construct variables which count the number of chargers within a number of speed bins with cutoffs of 50, 150, 250, and 500 kW. These bins are motivated by the bunching of charging speeds in the data.

I utilize the OSM data to speak to location characteristics. Specifically, I create indicator variables for the presence of various major road types (Autobahn, trunk, primary, secondary) within 1 km of each station. Additionally, I create indicator variables for whether the charger is located at an Autobahn service area or an unmanaged, non-Autobahn rest area. Service and rest areas are located right off the highway, offering a convenient place to stop. Service areas offer a number of amenities (food, restrooms, etc.), whereas rest areas tend to be rudimentary and offer only basic amenities.

Additionally, I construct indicators for the presence of various amenities within 250m of the charging station. Specifically, I include the following amenity types (as reported in the OSM data): fuel, fast food, restaurant, cafe, toilets, motel, hotel, gas, convenience store, supermarket, variety store, greengrocer. Due to the complexity and heterogeneity of amenities, I don't include detailed information about nearby amenities (e.g. I cannot model the effect of being by McDonalds vs. Burger King separately). These are intended more as rough

[9]For robustness, I repeated the estimation procedure without the assumption of independence. I estimated a small, negative correlation of $\rho = -0.06$, suggesting that there is not much (if any) correlation.

proxies for the presence of nearby amenities which may draw consumers.

4.3 Market definition

The overlapping nature of commuting patterns makes market definition difficult in this setting. No matter what boundary one specifies to demark a market, there will always be some consumers from beyond that region who commute into it. For instance, a market boundary intersecting a major highway separates chargers into two separate markets. However, many consumers may pass by both chargers, so the two chargers should probably be considered as competing within the same market. Even if one distinguishes between city or highway chargers and classifies markets in this way, drivers commuting to and from the city (or between two nearby major cities) would potentially use chargers from both the highway and city markets.

This problem is inescapable, but I will aim to minimize it as much as possible by considering relatively broad markets. When constructing markets, I first use the EU's Functional Urban Area classification[10]. Functional Urban Areas (FUAs) are defined as cities and their associated commuting zone. In certain regions (e.g. the Rhine-Ruhr area), there are multiple FUAs located right by each other. As illustrated in Figure 4b, there are many overlapping commuting flows between metro areas in this region. Therefore, I decide to group adjacent FUAs together and define the convex hull of their union as a 'market'. I consider all chargers within this region as belonging to the same market and compute market shares accordingly. This setup minimizes the truncation issue to the extent possible.

For estimation, I use the Rhine-Ruhr, Frankfurt-Mannheim-Stuttgart, Munich, Thuringia, and Hamburg regions. These regions together account for around 54 percent of total German EV registrations and 48 percent of fast charging stations. These markets are chosen because they represent major commuting markets and are distinct from each other and their surrounding regions.

4.4 Demand estimation

Given an initial value of nonlinear parameters, I solve for the vector of station mean utilities $\boldsymbol{\delta}$. I first initialize a guess of $\boldsymbol{\delta}_0$. Given this $\boldsymbol{\delta}_0$, I solve consumers' utility maximization problem and obtaining the resulting market shares. I then update the guess of $\boldsymbol{\delta}_t$ using the SQUAREM quasi-Newton algorithm to accelerate the BLP contraction. I iterate until $\|\boldsymbol{\delta}_t - \boldsymbol{\delta}_{t-1}\|_\infty < \epsilon$. For now, I use $\epsilon =$`1E-8`.

I then project $\boldsymbol{\delta}$ on station and location characteristics as well as a network fixed effect, with m representing the CPO operating station j:

$$\delta_j = \beta X_j + \nu_m + \xi_j$$

[10]https://ec.europa.eu/eurostat/statistics-explained/SEPDF/cache/72650.pdf

I then use the residual $\xi_j(\theta)$ interacted with a number of instruments Z_j to form the station demand moments:

$$g_{\text{dem}}(\theta) = Z_j' \xi_j(\theta)$$

For instruments, I find all chargers within 100 m, 333 m, 1 km, and 5 km of each charging station. Within each ring, I compute the number of stations, the number which offer rapid charging (speed greater than 150 kW), the average station size, and the average station maximum speed. These instruments will be proxies for the presence of local competition, as well as the average quality of these competitors.

4.5 Micro moments

I construct a number of moments using the consumer micro data.

I construct moments based on public fast and slow charging shares for each type. Additionally, I include moments for the work charging share for type hw. Since fast and slow charging are already included for type w, including the work charging share for them would be redundant. Similarly, including home charging shares would be redundant for types h and hw. I also construct moments based on the standard deviation of the public charging share for each type. This disciplines the model to better match the shape of the public charging share distribution in the data. For all type-specific moments, I weigh by the proportion of consumers who have each type.

In the micro data, I observe the work charging share conditional on the binned price difference between work and home charging. I construct a separate moment for each price difference bin. I construct a moment matching the observed work charging share for all consumers with a (simulated) work price difference within each bin. I also construct a moment based on the proportion of consumers who select a paid plan from each provider. As I unfortunately don't see this conditional on type, these moments are not conditional on type.

I form the micro moment vector $g_{micro}(\theta)$ by stacking all of these moments together.

4.6 Supply side

On the supply side, for CPOs which do not offer plans, I invert their first order condition to obtain the model-implied marginal costs. I only do this for the networks which do not offer menus of two part tariffs. I then compute the difference between the implied marginal cost and the commercial electricity price corresponding to the network's level of aggregate demand, net of the GHG quota credit value.

$$g_{mc}(\theta) = \begin{bmatrix} \hat{c}_1(\theta) - c_1 \\ \vdots \\ \hat{c}_{N_m}(\theta) - c_{N_m} \end{bmatrix}$$

To be clear, $g_{mc}(\theta)$ does not contain entries for CPOs that offer plans. Those networks are dealt with separately.

For the networks which offer plans, I construct moments based on the first order conditions for each of their decision variables (basic price, paid plan prices, and plan fees), assuming that their marginal cost is equal to the electricity prices corresponding to their aggregate electricity usage (and utility vs. non-utility status). This gives me three sets of moments for each plan-providing CPO: $f^{\text{Basic}}(\theta)$ (FOC for the basic fee), $f^{\text{Paid}}(\theta)$ (FOC(s) for the plan price(s)), and $f^{\varphi}(\theta)$ (FOC(s) for plan fee(s)). I stack these up for all providers to form $g_{FOC}(\theta)$. As an example with CPOs A and B and one plan tier for each:

$$g_{FOC}(\theta) = \begin{bmatrix} f_A^{\text{Basic}}(\theta) \\ f_A^{\text{Paid}}(\theta) \\ f_A^{\varphi}(\theta) \\ f_B^{\text{Basic}}(\theta) \\ f_B^{\text{Paid}}(\theta) \\ f_B^{\varphi}(\theta) \end{bmatrix}$$

4.7 GMM objective

The moment vector used for estimation is formed by stacking each of the separate moment vectors (demand moments, micro moments, marginal cost moments, and the FOC moments):

$$g(\theta) = \begin{bmatrix} g_{dem}(\theta) \\ g_{micro}(\theta) \\ g_{mc}(\theta) \\ g_{FOC}(\theta) \end{bmatrix}$$

The GMM objective function is formed using optimal weighting matrix $W = S^{-1}$, where S indicates the variance-covariance matrix of $g(\theta)$:

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\, g(\theta)' W g(\theta)$$

I search for the θ which minimizes the objective using Nelder-Mead.

4.8 Identification of the price coefficient

One may be inclined to wonder how I can identify the price coefficient in this model. Indeed, I see no price variation over time or within networks, and the price that consumers pay is endogenously chosen by the consumer (in terms of the plan prices). While my identification argument will be non-standard, I will argue that I can actually identify the price coefficient pretty well.

While I do not see price variation within networks or over time, there is a massive amount of choice set variation within each market. Variation in consumers' choices when presented with different networks and stations will help identify the price coefficient. Additionally, as prices are uniform within each network, variation in station characteristics within a network (e.g. station size, charging speed, location quality) provide an additional source of variation to identify the price coefficient.

Furthermore, the supply side moments provide another key source of identifying variation. By imposing that the model-implied marginal costs coincide with the distribution of commercial electricity prices, the price coefficient is indirectly identified. The plan charging price and monthly fee first order conditions act as an additional source of identification (for both α as well as α_{plan}). If these moment conditions are far from being satisfied, it is likely that the proposed value of the price coefficient is far from the true value.

Finally, the price coefficient is also identified by matching the share of charging done at work as a function of the price difference between work and home charging. This provides an additional source of variation to help identify preferences. It is also a bit more 'outside' of the model and functions somewhat as a test of external validity (in that I'm not merely relying on the supply side moments for identification).

5 Results

I present the estimated nonlinear parameters in Table 8. All of the coefficients have the intuitive sign: drivers have downward sloping demand, prefer faster chargers, and rank home, work, and public slow charging in the same order observed in the survey data.

Coef	Estimate	SE
$\hat{\alpha}$	0.478	0.009
$\hat{\alpha}_{plan}$	0.227	0.009
$\hat{\alpha}_{mileage}$	-0.547	0.026
$\hat{\beta}_{detour}$	-0.332	0.023
$\hat{\beta}_{speed}$	0.136	0.027
$\hat{\sigma}_{loc}$	0.856	0.002
$\hat{\sigma}_{priv}$	0.813	0.007
$\hat{\sigma}_{speed}$	0.840	0.005
$\hat{\sigma}_{paid}$	0.458	0.037
$\hat{v}_h$	-1.699	0.153
$\hat{v}_w$	-1.842	0.152
$\hat{v}_s$	-2.039	0.152

Table 8: Nonlinear parameter estimates

5.1 Elasticities

Without context, it is difficult to jointly interpret the parameter estimates in Table 8. One of the key questions is whether the model delivers reasonable price elasticities. To address this, I present station-level price elasticities in Table 9. These are computed by assuming that charging prices at all levels (both basic and plan) change (rather than, for instance, only changing the basic price while keeping the paid plan price fixed). I find an average price elasticity of -1.79, suggesting that consumers are quite responsive to price. The standard deviation is 0.37, indicating that there is substantial heterogeneity at the station level. These results are in line with those from Bernard et al. 2025, who document short-run elasticities ranging from -2.9 to -2 in a large-scale randomized control trial for UK public fast chargers.

Outside option	Mean	SD	p10	p25	p50	p75	p90
Home & Work	-1.88	0.36	-2.34	-2.05	-1.92	-1.69	-1.39
Home	-1.84	0.37	-2.30	-2.04	-1.90	-1.62	-1.32
Work	-1.85	0.43	-2.34	-2.06	-1.93	-1.66	-1.35
Neither	-1.73	0.42	-2.23	-1.99	-1.81	-1.48	-1.20
Aggregate	-1.79	0.37	-2.25	-2.01	-1.85	-1.57	-1.28

Table 9: Station-level elasticities, presented in aggregate as well as by consumer type (hw, h, w, n).

It is also interesting to break down elasticities based on consumer type. Perhaps not surprisingly, hw consumers are the most elastic (-1.88), and n consumers are the least elastic (-1.73). Consumers with the largest set of alternative options are the most sensitive to public charging price since their other options are cheaper and more convenient. Type n consumers, who have no alternative other than public slow charging, are the least sensitive with regard to price.

I find rather unsurprisingly that consumers are more likely to substitute between nearer chargers than between farther ones. In Figure 9, I plot the average diversion ratio as a function of distance (km) between stations. I find that cross price elasticities decay quickly in the distance to the rival station, as expected. This is a composition of two effects: 1) nearby stations are likely to have more consumer choice sets in common, and 2) given that two chargers are in the same choice set, consumers will be less likely to substitute to station that requires a greater detour from their route (all else held equal).

I also document heterogeneous preferences for charging speed based on the maximum charging speed of consumers' vehicles. In Figure 9, I plot station price elasticities as a function of the station's maximum power rate (in kW), separately for each vehicle charging power bin. Consumers with slower charging vehicles have less elastic demand for slower chargers and more elastic demand for faster chargers. The relationship flips for faster charging consumers: they have more elastic demand for slower chargers and less elastic demand for fast

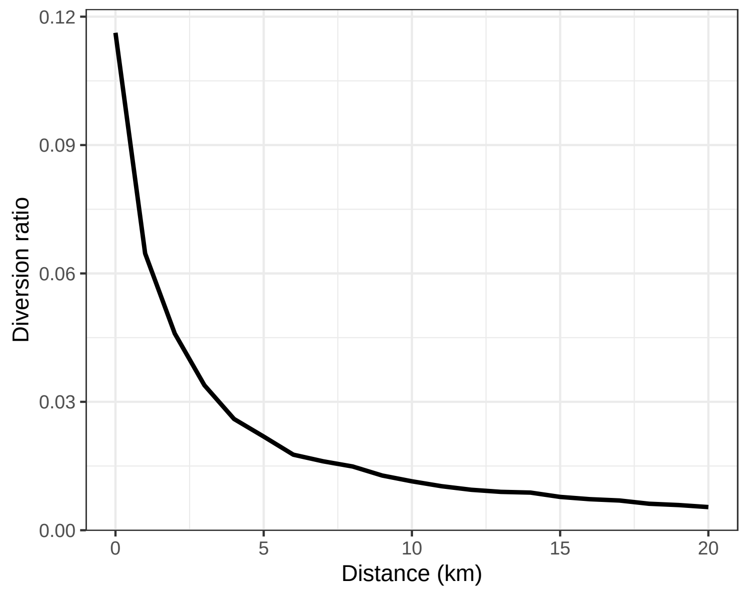


Figure 8: Mean diversion ratio as a function of distance between stations. The mean diversion ratio within each 500 meter distance bin is plotted.

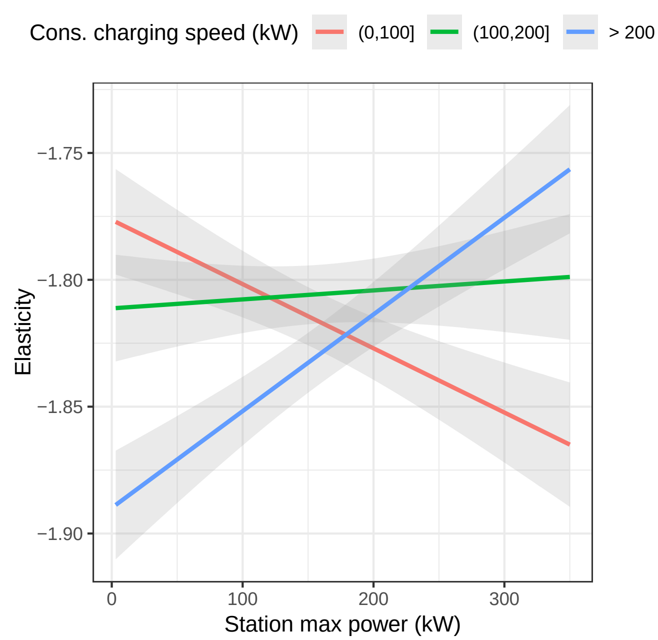


Figure 9: Station price elasticity by station max charging power (kW) and consumer binned maximum charging speed (0 to 100 kW, 100 to 200kW, and greater than 200 kW). For each consumer charging speed bin, I regress the station price elasticity on the station's max power.

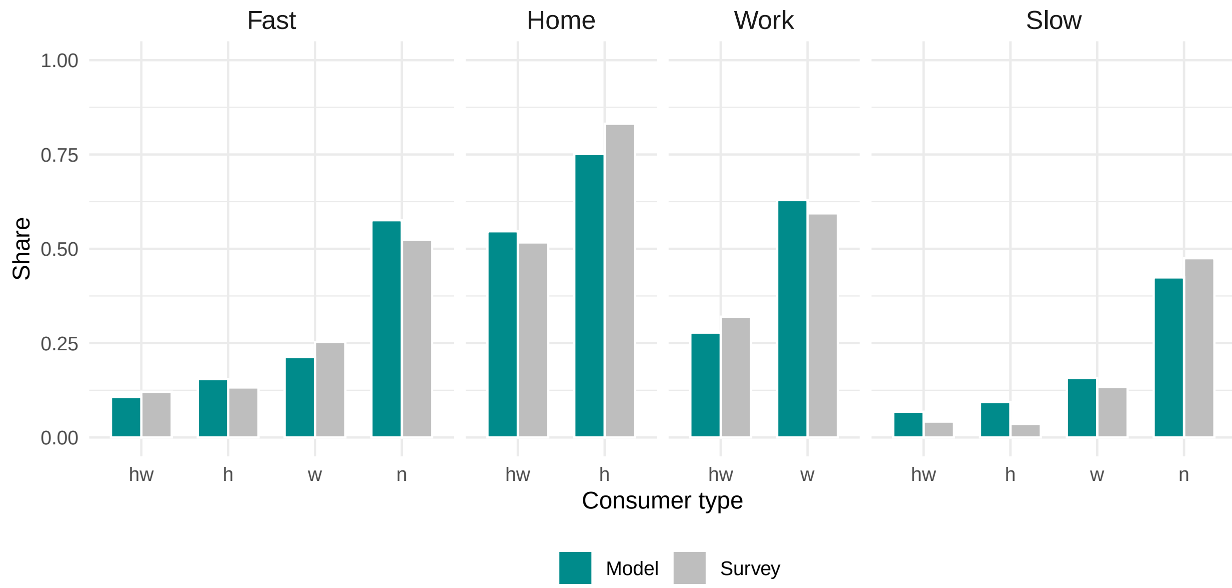


Figure 10: Comparison of model-predicted and empirical charging shares at each charging type (fast, home, work, slow) across each consumer type (hw, h, w, n). The model-predicted shares are indicated in cyan, while their sample analogues are indicated in grey. Each group of bars corresponds to a given consumer type. The type of charging is indicated at the top of each plot panel.

chargers. This relationship is expected. Consumers with fast charging vehicles experience time savings from faster chargers and are willing to pay more for them, while consumers with slow charging vehicles gain virtually no benefit from faster charging.

Variation in vehicle charging speed creates heterogeneous preferences for speed and, therefore, heterogeneous substitution patterns. Vehicle charging speed controls the level of perceived quality differentiation between charging stations and networks. Faster charging consumers have stronger preferences for speed and therefore tend to pick faster stations. Slower charging consumers experience little variation in charging speed, causing them to care less about speed differences in their station choice.

5.2 Goodness of fit

Given the significant degree of consumer heterogeneity and its impact charging demand, it is worth assessing how well the model can match observed variation in consumer charging decisions. Figure 10 compares model-predicted charging shares for each charging option with their sample analogue for each consumer type. The model is able to match charging shares for each type of charging quite well, both for fast charging as well as each of the outside options. It explains much of the heterogeneity in charging behavior across types.

Table 10 compares model-predicted fast charging shares for different consumer mileage bins with those observed in the survey data. Even though these moments were not targeted in estimation, the model is able to rationalize the increased share of public fast charging as mileage increases and how it varies with type. The model does especially over-predict fast charging shares for low mileage h consumers (13% compared with 8% in the data), but the disparity decreases as mileage increases. It also over-predicts for n type consumers with mileage between 10 and 20 thousand kilometers, but this is mainly because of the non-monotonicity in the micro data itself.

	hw		h		w		n	
Mileage	Survey	Model	Survey	Model	Survey	Model	Survey	Model
$(0, 10000]$	0.08	0.09	0.08	0.12	0.20	0.17	0.54	0.50
$(10000, 20000]$	0.12	0.11	0.14	0.16	0.24	0.22	0.48	0.60
$(20000, \infty]$	0.14	0.15	0.19	0.20	0.32	0.29	0.63	0.66

Table 10: Share of model-predicted public fast charging by consumer type and binned annual mileage, compared with observed public fast charging shares in the survey.

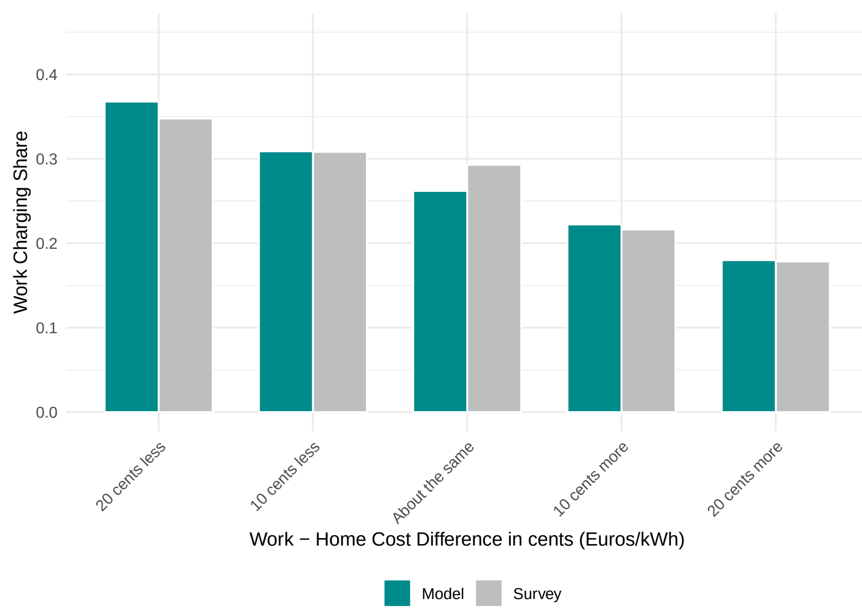


Figure 11: Work charging share as function of the price difference (in cents €/kWh) between work and home charging costs. The cyan bars correspond to the model-predicted work shares, while the grey bars correspond to their empirical analogues in the micro data. Each set of bars corresponds to the difference between work and home charging costs, binned in 10 cent increments. The comparison is done on the subset of consumers who have charging both at home and at work ($N = 395$).

Finally, Figure 11 compares the predicted work shares as a function of the difference between (simulated) work and home charging prices with their sample analogues. In the micro data, I observe that the share of charging done at work decreases as work charging becomes more expensive relative to home charging. The model is able to replicate this relationship well and predicts a similarly declining share of work charging. This demonstrates that the estimated price coefficient and nesting parameters generate plausible substitution patterns for the outside option.

6 Counterfactual analysis

The goal of this paper is to decompose the contributions of network structure and price discrimination to market power. To this end, I simulate the effect of two different policies. First, I ban price discrimination and assume that each CPO may only set one linear price for all consumers. This shuts down the plans offered by the plan-offering networks and puts all networks on even footing. I then compute the equilibrium prices resulting from this new assumption on market structure.

The second policy randomly changes network structure by swapping stations of the plan-offering networks (EnBW, Ionity, and Aral) with non-plan networks. I assume that the plan networks still engage in price discrimination using subscription plans. This is a rather extreme scenario which serves to isolate the role of network structure. It explores how these networks' pricing behavior would change if their station location and quality were more akin to other networks while keeping their network size constant.

Finally, I simulate the joint effect of these policies. By comparing the simultaneous effect of banning price discrimination ***and*** shuffling network structure to either scenario independently, I can quantify the extent to which network structure is complementary with price discrimination.

6.1 Banning price discrimination

In this counterfactual scenario, I ban price discrimination by shutting down subscription plans. Instead, all CPOs must set one linear price for all consumers. I solve for equilibrium prices by iterating on the pricing FOC equation until convergence:

$$\boldsymbol{p} \leftarrow \boldsymbol{c} + \eta(\boldsymbol{p})$$

where $\boldsymbol{c}$ represents the vector of CPO costs and $\eta(\cdot)$ represents the vector of markups. Banning price discrimination causes a reduction in prices industry-wide. The sales-weighted average price decreases by 9%. Plan-offering networks decrease prices by 5.9%, while non-plan networks decrease their price by 10.7%.

The aggregate quantity of charging increases by 5.5%. Quantity falls by 4% for plan-offering CPOs and increases 13.4% for non-plan CPOs. This represents a reallocation of demand between plan and non-plan networks.

Finally, profits are lower for both plan-offering and non-plan networks. Profit falls by 18.2% for plan-offering CPOs, driven by both the reduction in the linear price and lost plan fee revenue. Aggregate profit for non-plan CPOs falls by 3.2% with the reduction in charging prices offsetting increased demand.

On the consumer side, I find that the vast majority of consumers benefit from the elimination of price discrimination, while a small number of consumers are worse off under the policy. This is a bit counter-intuitive: we would expect that consumers who subscribed to a network would be worse off after the elimination of price discrimination. Instead of paying the discounted rate, they must now pay the network's higher regular rate. However, two effects explain this result. The first is the fact that once plans are shut down, plan-offering CPOs decrease their linear prices. This lowers the magnitude of the price increase the subscriber faces. The second is the fact that other networks respond to the plan elimination by also reducing their prices. When consumers can re-optimize their demand, they are able to lower their charging costs.

In conclusion, eliminating price discrimination decreases charging prices industry-wide and increases overall output.

6.2 Shuffling network structure

I randomly swap the locations of EnBW, Ionity, and Aral Pulse with stations of other networks. This is done by swapping the ownership matrix for each of the charger pairs. Swapping stations in this manner ensures that network sizes remain the same, while the quality of a CPOs locations will change. I then compute the new equilibrium prices and fees given the new charging network structures. I iteratively updating firms' prices and fees (if applicable) using best responses until both prices and fees converge to the new equilibrium.

I find that non-subscriber prices for plan-offering CPOs decrease by an average of 4.3% relative to baseline. Non-plan CPOs increase their prices slightly by an average of 0.79%. By taking 'good' stations from top networks and giving them to rival networks, this intervention acts as a transfer of market power between plan-offering CPOs and non-plan CPOs. Demand increases by 23.6% for non-plan networks, while profits increase by 24.2%. Conversely, demand decreases by 41% for plan-offering networks, while their profits decrease by 36.4%. Together, these findings suggests that the advantageous locations of plan-offering networks allow them to exercise market power. When these locations are handed over to other networks, the other networks benefit significantly.

6.3 Combined effect

I finally consider the effect of combining station reallocation with the elimination of price discrimination. The station reallocation follows the same procedure outlined in the previous section. As before, I solve for equilibrium prices under the assumption that CPOs only set one linear price for all consumers. I iteratively solve for equilibrium prices using the Bertrand-Nash markup formula.

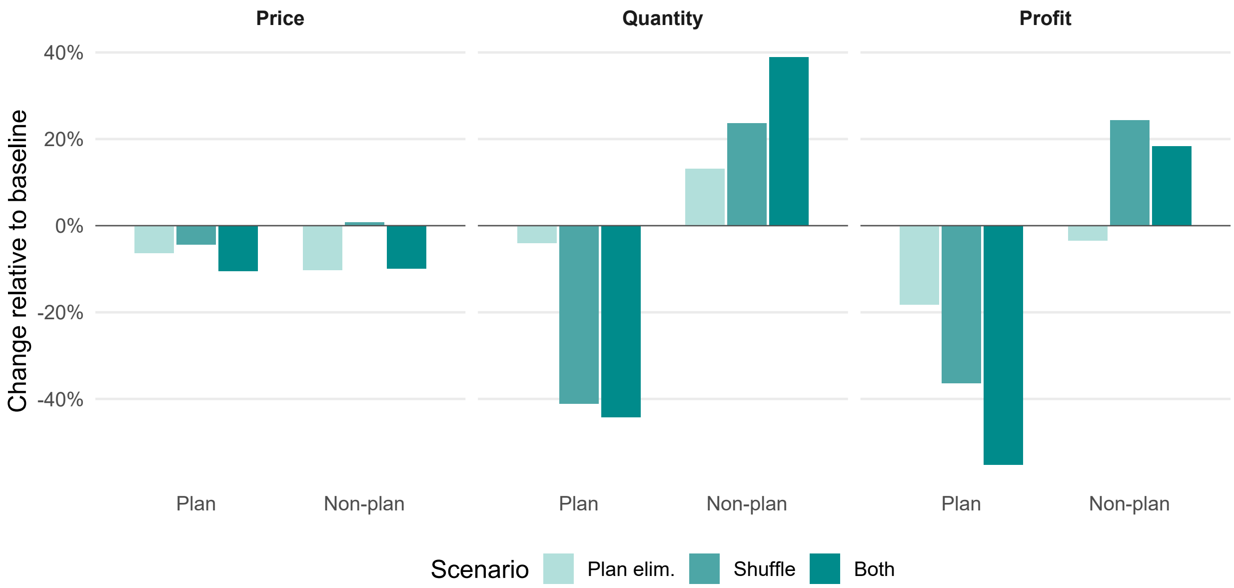


Figure 12: Effect of three counterfactual scenarios on market outcomes (price, quantity, and profit). Outcomes are aggregated by plan and non-plan network status. The first scenario is the elimination of price discrimination. The second scenario is swapping plan-offering CPOs' stations with those of non-plan CPOs. The third scenario combines these two policies.

I find that plan-offering CPOs reduce their linear price by 5.4% and experience significantly lower demand (−44.2%) and profits (−55.2%). There are two ways of thinking about this. First, consider the effect of banning price discrimination with and without shuffling station locations. As expected, eliminating price discrimination results in lower profits. However, profits decrease even further when network structure deteriorates. In other words, when these networks retain advantageous locations, the impact of banning price discrimination is mitigated. Or, consider the effect of shuffling station locations. When they lose 'good' locations, these networks' profits will decrease significantly. However, when they are still allowed to discriminate, the impact of this intervention is lessened. In other words, price discrimination amplifies advantages in network structure.

This illustrates the complementarities between network structure and price discrimination: the impact of losing advantageous network structure is worsened when firms are not allowed to price discriminate. The converse is also true: advantageous network structure enhances the gain from price discrimination.

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A Station map

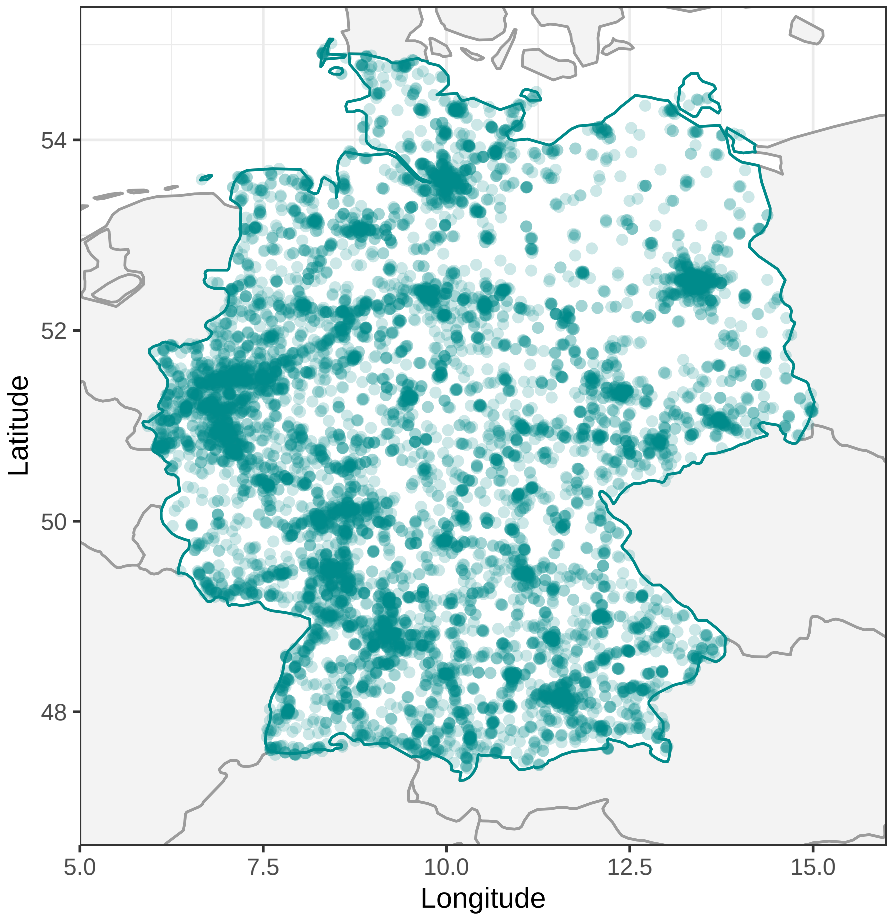

Figure 13: Map of all fast charging points in my sample as of September 2024.

B Concentration metrics for Autobahn chargers

		Min	Q1	Median	Mean	Q3	Max
$k = 400$	Stations	1.00	4.00	7.00	7.70	10.00	33.00
	Networks	1.00	3.00	5.00	5.67	7.00	18.00
	HHI	1420.01	2562.82	3417.39	4039.10	5018.44	10000.00
		Min	Q1	Median	Mean	Q3	Max
$k = 200$	Stations	2.00	8.00	13.00	15.40	19.00	60.00
	Networks	2.00	6.00	9.00	9.43	12.00	24.00
	HHI	979.33	1854.72	2401.18	2730.07	3241.09	7347.49
		Min	Q1	Median	Mean	Q3	Max
$k = 100$	Stations	4.00	16.00	27.00	30.81	37.25	108.00
	Networks	3.00	11.00	14.00	14.85	20.00	30.00
	HHI	835.09	1536.27	1811.95	2022.86	2276.75	6316.98

Table 11: Summary statistics of the number of stations, number of networks, and HHI at the cluster level during September 2024 for Autobahn-adjacent chargers (within 1 km). Clusters of stations are assigned using k-means clustering for $k \in \{100, 200, 400\}$.

C Network charging speeds

Network	Mean	SD	Min	Q25	Median	Q75	Max	N
EnBW	219.72	99.00	50	150	300	300	400	1367
Aral Pulse	253.38	71.31	50	150	300	300	400	429
IONITY	352.70	11.34	350	350	350	350	400	148
EWE	197.13	77.41	50	150	150	300	400	604
Lidl	57.41	32.18	50	50	50	60	400	461
Shell Recharge	263.07	93.14	50	150	300	360	475	363
Kaufland	55.84	19.77	50	50	50	60	350	317
Allego	167.88	81.89	50	150	150	150	300	411
ALDI South	124.66	42.31	50	100	150	150	200	247
E.ON	112.89	66.59	50	50	100	150	400	323

Table 12: Summary statistics of maximum station power (in kW) for the top 10 networks as of September 2024.

Network	Mean	SD	Min	Q25	Median	Q75	Max	N
EnBW	186.29	105.92	2.3	150	150	300	400	8624
Aral Pulse	225.34	95.09	22	100	300	300	400	3605
IONITY	347.53	33.39	200	350	350	350	400	1254
EWE	204.70	100.13	11	150	150	300	400	1970
Lidl	47.76	38.45	11	27.25	50	60	400	1546
Shell Recharge	257.54	101.65	22	150	300	360	475	1772
Kaufland	44.73	22.61	11	22	50	60	350	1213
Allego	162.14	101.74	11	50	150	300	300	2124
ALDI South	93.14	56.84	11	50	100	150	200	888
E.ON	99.62	91.81	2.3	22	75	150	400	1393

Table 13: Summary statistics of charging-port level maximum power (in kW) for each of the top 10 networks as of September 2024.

D Commercial electricity prices

The most critical input to a fast charger is electricity. In order to model the supply side, I must account for the cost of electricity. The challenge in doing so is that I do not observe the prices that charging networks pay. Instead, I must infer it from available data.

In Germany, the commercial electricity price has several components: the wholesale price, grid fees, surcharges, and taxes. The wholesale price commonly accounts for less than half of the actual price paid by the end consumer. A summary of the electricity prices for German non-household electricity consumers in the second half of 2024 is given in Table 14.[11] In the table, the first column indicates the consumers' binned level of annual usage. The second column lists the average price without any taxes, fees, or other surcharges. The third column lists the average price inclusive of VAT. The fourth column lists the average price inclusive of both VAT as well as mandatory levies and fees.

From this table, it is evident that the price paid by commercial consumers is decreasing in annual usage. To put these numbers in context of charging network, a small or medium sized network (annual demand between 2 and 20 thousand MWh) would pay 6.78 cents more per kWh (approximately 36% higher) than large networks (annual demand between 70 and 150 thousand MWh).

In my analysis, I will assume that a charging network receives the average electricity price based on its (realized) aggregate usage level. The assumption here is that a charging network will choose a contract with one provider to supply their entire network's charging needs. This is a reasonable assumption given the nature of the German electricity market.

The German electricity market was deregulated in 1996. This spurred significant entry on both the generation and retail side. Today, the market features a large number of retail power providers: in 2023, 93% of grid areas have at least 20 electricity providers, and 72%

[11] https://www-genesis.destatis.de/datenbank/online/url/3d80e83e

Quantity bin (MWh)	Price(€/kWh)	Price (€/kWh) (w/VAT)	Price(€/kWh) (w/ VAT, levies, fees)
(0, 20]	0.2820	0.3326	0.3958
(20, 500]	0.2302	0.2714	0.3233
(500,2,000]	0.2010	0.2359	0.2834
(2,000, 20,000]	0.1810	0.2076	0.2552
(20,000, 70,000]	0.1509	0.1712	0.2156
(70,000, 150,000]	0.1313	0.1430	0.1874
>150,000	0.1323	0.1390	0.1851

Table 14: Average German commercial electricity price per kWh (in Euros) by electricity usage bin during the second half of 2024. The first column corresponds to the user's annual level of electricity usage. The second column lists the average price per kWh without any taxes, fees, or other surcharges. The third column lists the average price per kWh inclusive of VAT. The fourth column lists the average price per kWh inclusive of both VAT as well as mandatory levies and fees.

of grid areas have more than 100 electricity providers [12] The wide variety of retail power providers is facilitated by the fact that the country is treated as a single market with a single wholesale price. As such, a commercial consumer is able to choose a contract with one provider to meet their network-wide electricity needs. This avoids the need to negotiate separate contracts with countless different providers across regions they serve.

Of course, it is also possible for charging networks to purchase electricity on the futures market to reduce exposure to wholesale price volatility. Additionally, networks sometimes choose to supply power from 100% renewable energy (by sourcing power from suppliers which offer such a mix or using power purchase agreements). Both of these behaviors are unobserved to me, so I abstract away from these considerations in my model.

[12] https://www.smard.de/page/home/topic-article/211972/212104

E Car mode choice probability

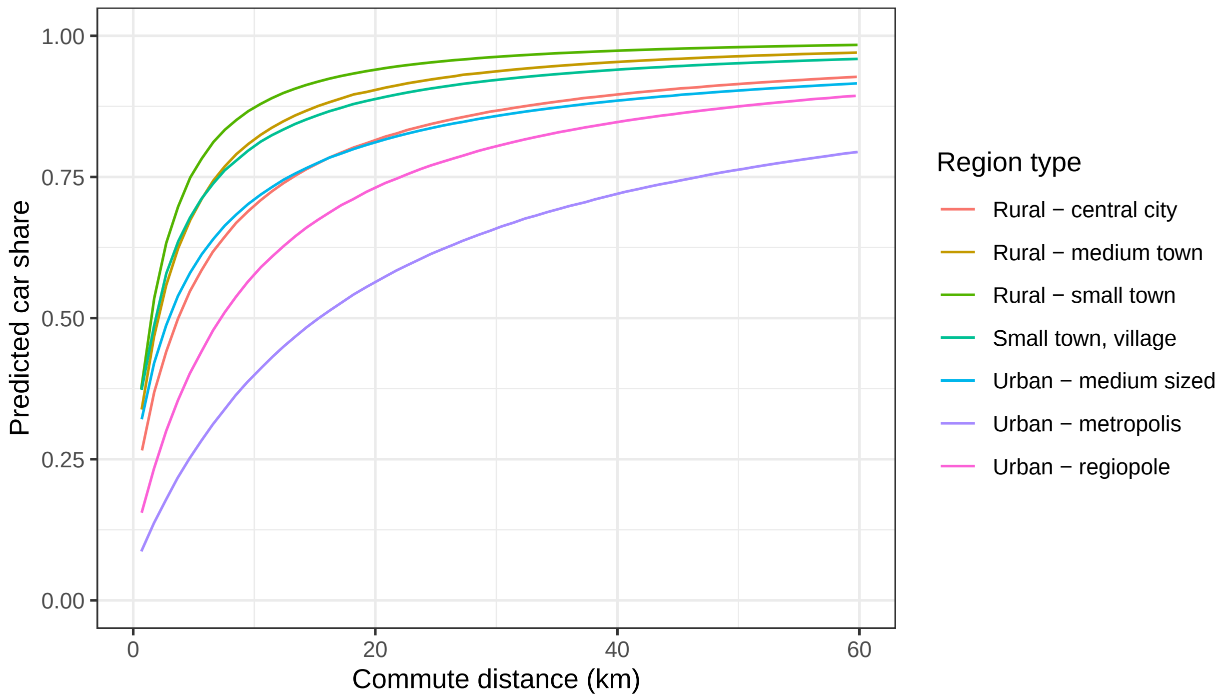

Figure 14: Predicted share of commuting trips taken by car as a function of trip distance and origin region type

F Annual mileage and range correlation

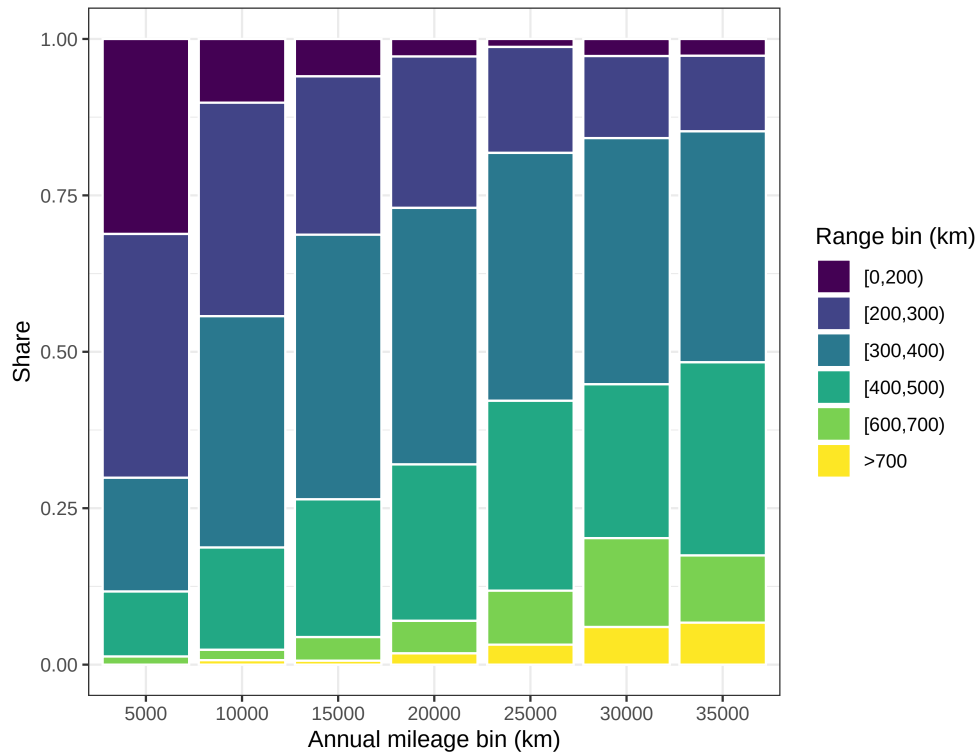

Figure 15: EV range distribution conditional on annual mileage. The data is from the US-CALE EV driver survey. The x-axis plots binned mileage (in 5,000 kilometer increments), while the y-axis represents the share of drivers in each mileage level with an EV with the designated range. The color indicates the EV's range (in kilometers), binned in 100km increments.

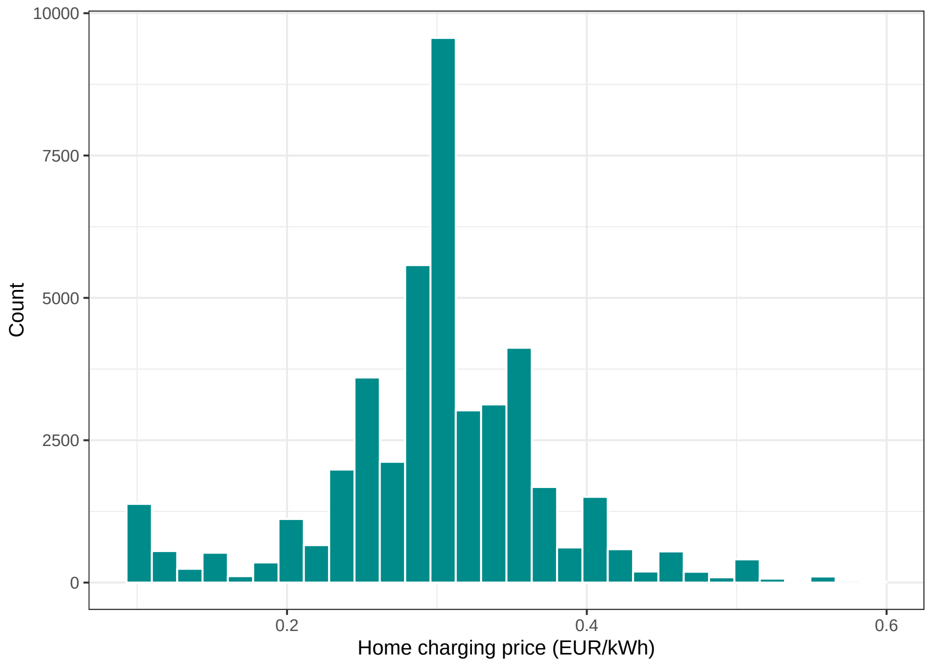

Figure 16: Histogram of home charging prices per kWh (2022)

G German home charging survey

The German National Center for Charging Infrastructure (Nationale Leitstelle Ladeinfrastruktur) conducted a survey of recipients of the Federal Ministry of Transport and Digital Infrastructure's KfW 440 home charging subsidy program. The program gave a €900 for the installation of a private charging wallbox. Over 690,000 charging points were installed through the program. 200,000 recipients were randomly selected between September and October of 2022 to complete a survey regarding their home charging behavior, of which 51,893 responded.[13]

The survey asked them about the wallbox installation process (cost, difficulty), property type and location, vehicle ownership and mileage, and charging behavior. Importantly, the survey reports the household's per-kWh charging price. This is very useful for my analysis, as it allows me to incorporate heterogeneity in the value of charging at home into my model.

The distribution of home charging prices reported in the survey are reported in Figure 16. The mean is around €0.31/kWh, while the standard deviation is around €0.06/kWh. This is a significant amount of dispersion. One may think that this variation could be explained by differences in geography or city type. However, Table 15 shows that there is very little difference across region types - rather, most of the dispersion is *within* the region itself.

Why is there so much dispersion in a household's charging price? The short answer is that the German electricity market is one large grid with many public utility companies. The

[13] https://nationale-leitstelle.de/wp-content/uploads/2024/10/Studie_Einfach_zu_Hause_laden.pdf

Region type	Mean	SD	N
Metropolis	31.08	5.92	2812
Major city, urban	31.21	6.14	4061
Medium city, urban	31.01	6.01	13828
Small town, urban	30.86	6.05	4479
Central rural city	31.21	6.08	1964
Medium rural city	31.06	6.01	6473
Small rural city	31.21	6.18	7961

Table 15: Mean and standard deviation of household electricity prices across region types (2022)

entire market has one wholesale price, rather than location-specific nodal prices like in the United States. While grid fees paid to grid operators can vary across regions, the underlying cost of power is the same.

Additionally, the massive number of public utility companies means that consumers in every market have many provider options. 93% of grid areas have at least 20 providers, and 72% have more than 100 providers.[14] There is a lot of dispersion in the contract offers across providers. Prices per kWh varies based on annual usage levels, energy composition (some offer 100% renewable power), and pricing structure (trading off between a higher upfront fee and the linear price per kWh).

[14] https://www.bdew.de/media/documents/BDEW_Strompreisanalyse_102025.pdf