Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles*

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Abstract

This paper develops a structural model of endogenous product attribute choice in the presence of indirect network effects to study electric vehicle (EV) subsidies. Using data on the German EV market, I find that a support scheme almost doubled EV sales but substantially affected the price and driving range of EVs. When designing subsidies, these adjustments create a trade-off between optimizing different policy objectives. Large purchase subsidies maximize EV sales, whereas large charging station subsidies maximize consumer and total surplus. The results suggest that maximizing EV sales can lead to unintended consequences in the form of price and range adjustments.

Keywords: electric vehicle, endogenous product choice, indirect network effects, subsidies

JEL Codes: D12, D62, H23, L62, Q55

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1 Introduction

Road transport accounts for 12% of global greenhouse gas emissions and electric vehicles (EVs) are considered one of the most promising means to help decarbonize this sector. As a consequence, governments worldwide subsidize EV purchases, with total spending amounting to $15 billion in 2018. To aid the development of EVs, policymakers need to consider two fundamental issues. First, the driving range of EVs is lower than that of traditional gasoline or diesel cars, making it an important dimension of quality. Firms can adjust the range relatively easily, meaning they can respond with price and range changes to subsidies. Second, widespread adoption of EVs requires the development of a network of charging stations whose value depends on the number of EVs circulating. The presence of these indirect network effects creates a "chicken-and-egg" problem in which neither side of the market will develop without the other. Consequently, understanding how price and range decisions of firms interact with indirect network effects and affect market outcomes is crucial for evaluating EV policies.

This paper provides a framework to study subsidy design in the presence of adjustable product attributes and indirect network effects. Doing so is challenging and requires a framework with two innovative features. First, my framework allows for endogenous choices of both EV price and range. This is a nontrivial contribution as the current literature studying EV subsidies abstracts away from modeling range choices and in some cases does not model the car supply side at all. Modeling price and range choices is important as firms can alter these attributes in response to subsidies. Second, my framework incorporates indirect network effects and their interaction with endogenous price and range choices. Incorporating indirect network effects is challenging because they can lead to electric cars acting as complements. In that case, firms face an incentive to increase sales in order to spur additional entry of charging stations. Firms can do so by lowering the price of their EV or increasing the range; what strategy they choose is an empirical question as it depends on preferences and cost structures. My framework allows me to evaluate subsidy schemes as it links the price and range effects of subsidies to market outcomes. I can thus inform policy discussions and provide answers to questions such as: How do indirect network effects affect price and product attribute decisions of firms? How do subsidies affect EV prices and range, charging station entry, and policy objectives?

I find that purchase subsidies introduce strong price and range adjustments. Important network effects present on the EV demand and the charging station entry side amplify these adjustments. Indirect network effects lower EV markups by around 6% on average. These strategic supply-side reactions have important implications for subsidy design. Concentrating subsidy spending on purchase subsidies leads to large EV sales but causes strong price and range adjustments as firms respond by selling cheaper, low-range EVs. Concentrating subsidy spending on charging station subsidies generates fewer EV sales than purchase subsidies do, but also causes fewer range adjustments and delivers a larger charging station network, which maximizes consumer surplus. As a consequence, policymakers face a trade-off between maximizing EV sales, maximizing total and consumer surplus, and minimizing CO2 emissions, which are minimized by distributing spending between purchase and charging station subsidies. These findings highlight the importance of modeling price and range adjustments to subsidies. Doing so is especially important when policymakers want to maximize EV sales, as this can lead to unintended consequences in the form of price and range changes.

To answer my research questions, I build a structural model of car demand, car supply, and charging station entry. The demand side of the model builds on the canonical model of Berry, Levinsohn, and Pakes (1995). Consumers choose between differentiated cars of different engine types and exhibit preferences over EV range and the number of public charging stations. The demand side generates flexible substitution patterns, which are key to evaluating how purchase subsidies affect car choices. I account for the endogenous attributes with instruments exploiting the competitive environment and variations in charging station subsidies. The car supply–side builds on the recent literature studying equilibrium outcomes when firms can adjust one or more continuous product attributes (Fan, 2013; Crawford, Shcherbakov, and Shum, 2019) and extends it to model price and attribute choices when indirect network effects are present. Firms choose the prices of their cars and the range of their EVs. The charging station entry side links the number of charging stations to the cumulative EV base and the level of charging station subsidies. Modeling charging station entry allows me to incorporate indirect network effects into the car demand and supply model and study how charging station subsidies affect market outcomes. With this model, I can study how indirect network effects interact with endogenous price and range decisions and how these decisions affect the policy goals of EV subsidy programs. I estimate the model using a novel state-level data set of new car purchases and public charging station entry in Germany.

I find substantial indirect network effects on the EV demand and the charging entry side that make own-price elasticities larger in absolute value. Not accounting for indirect network effects would lead to overestimating EV markups. Also, indirect network effects lead to negative cross–price and positive cross–range elasticities, which has important implications for the price and range choices of EV producers. Negative cross-price elasticities mean that if a firm lowers the price of their EV, the demand for a competing EV may increase because the indirect network effects dominate the direct price competition effect. EV sales would almost double if producers internalized the effect of price and range choices on other EVs in the market, because firms would find it optimal to sell cheaper, lower–range EVs on which they earn a lower markup.

I use the model to perform a rich set of counterfactuals. I analyze a German program for purchase and charging station subsidies whose goal was to substantially increase EV sales. I find that this program increased EV sales by 75% but caused strong price and range adjustments. The indirect network effects increase these adjustments by only a small amount. Unlike in the case of uni-dimensional pass-through to price (Bulow and Pfleiderer, 1983; Stern, 1987; Weyl and Fabinger, 2013), the direction of the price and range effects is ambiguous and hence an empirical question. In this case, firms reduced the price and range and sold cheaper, lower-range EVs on which they collected a lower markup. I then analyze the effects of each part of the subsidy program individually. I find that removing the charging station subsidy would decrease EV sales by 18% and charging stations by 45%. Unlike the purchase subsidy, the charging station subsidy caused only minimal price and range adjustments. Removing purchase subsidies would decrease EV sales by 30% and charging stations by 4%. However, spending on charging station subsidies was larger in Germany.

I comprehensively analyze subsidy design in the next step by finding combinations of flat and range–based purchase and charging station subsidies that keep subsidy spending constant at the 2018 level. Such an exercise is of interest because it shows in detail how strategic reactions of firms to different subsidy schemes affect policy objectives. Also, different countries use different subsidy schemes, so the exercise can also inform policymakers in designing subsidies. I find that the policymaker faces a trade-off between maximizing EV sales, maximizing consumer surplus, and minimizing annual CO2 emissions from new cars. Whereas a large flat purchase subsidy maximizes EV sales at a lower range and prices, consumer surplus is maximized when almost all the budget is spent on charging subsidies. A larger purchase subsidy coupled with a lower charging subsidy minimizes CO2 emissions from new car sales. Firms respond to a larger flat purchase subsidy by selling cheaper EVs at a lower range and respond to lower flat subsidies or larger range–based purchase subsidies by selling more expensive EVs with a higher range. Overall, purchase subsidies lead to strong price and range adjustments. An increase in the station subsidy induces only small price and range adjustments but still increases EV sales through indirect network effects. These results have important implications for policymakers. They suggest that maximizing EV sales comes at the expense of a lower range and a smaller charging station network, and therefore at the expense of maximizing consumer surplus. Policymakers may want to carefully consider the benefits of increasing EV sales against the range adjustments such a strategy causes.

In this paper, I make contributions to several streams of literature. First, I contribute to the literature on EV policies by analyzing the role of indirect network effects in the price and range decisions of firms. This literature has studied the effects of purchase subsidies (Beresteanu and Li, 2011; Muehlegger and Rapson, 2022; Xing, Leard, and Li, 2021), the role of charging stations and indirect network effects (Li, Tong, Xing, and Zhou, 2017; Li, 2023; Springel, 2021; Fournel, 2023), and other margins such as entry of new EVs (Armitage and Pinter, 2022), usage behavior (Davis, 2019; Sinyashin, 2021), and portfolio effects (Johansen and Munk-Nielsen, 2020; Davis, 2022).[1] Jia Barwick, Kwon, and Li (2023) study attribute-based subsidies in China but do not model the interaction with the charging station side. To the best of my knowledge, this is the first paper to study strategic price and range responses to subsidies and also to model how these responses interact with indirect network effects. Doing so allows me to carefully study strategic reactions by firms to subsidies and how indirect network effects affect these reactions. Price and range adjustments can alter consumer choices and thus the effects of

[1] For an overview of this literature, see Rapson and Muehlegger (2023)

subsidy schemes. Second, I contribute to a wider literature studying environmental policies in car markets by offering a comprehensive evaluation of the economic effects of EV purchase and charging station subsidies. By studying strategic supply-side responses to subsidy schemes, I contribute to the strand of this literature that investigates supply-side effects of environmental policies (Knittel, 2011; Klier and Linn, 2012; Reynaert, 2021; Leard, Linn, and Springel, 2019). By comparing different EV subsidy schemes, I contribute to another strand that studies and compares the effectiveness of different policy tools (Pavan, 2017; Grigolon, Reynaert, and Verboven, 2018; Durrmeyer and Samano, 2018). Third, I contribute to two strands of the IO literature. First, my paper relates to the literature on attribute provision (Spence, 1975; Sheshinski, 1976; Mussa and Rosen, 1978; Maskin and Riley, 1984; Fan, 2013; Crawford et al., 2019) that studies how firms provide a product attribute (quality) in imperfectly competitive markets. Second, the paper also relates to the pass-through literature (Bulow and Pfleiderer, 1983; Stern, 1987; Kim and Cotterill, 2008; Weyl and Fabinger, 2013) studying how firms adjust prices in response to subsidies, taxes, or marginal cost changes. I contribute by bridging a gap between these two strands by providing a framework that allows for a multi-dimensional response in prices and product attributes to subsidies, taxes, and marginal cost changes in imperfectly competitive markets in which network effects are present. In this regard, my paper resembles the approach of Gaudin (2022) who provides a theoretical framework for predicting the directions of price and quality responses to subsidies, taxes, or marginal cost changes. Finally, I contribute to a recent literature endogenizing product attribute choice (Fan, 2013; Crawford et al., 2019) by allowing product attribute choices to interact with indirect network effects.

The paper is structured as follows: Section 2 describes the car industry in general and the EV industry in particular and the data used in the estimation. Section 3 describes the structural model and Section 4 outlines the estimation strategy. Section 5 presents the results from the structural model, Section 6 presents the results from the counterfactuals, and Section 7 concludes.

2 Industry Description and Data

The setting for the empirical analysis is the new car market in Germany. A special focus lies on the electric car market, including public charging stations. In past decades, the German new car market has been characterized by a predominance of combustion engine cars using gasoline or diesel as fuel. Simultaneously, sales of electric vehicles increased more than twenty-fold between 2012 and 2018, and the number of charging stations has increased by a factor of almost 15.

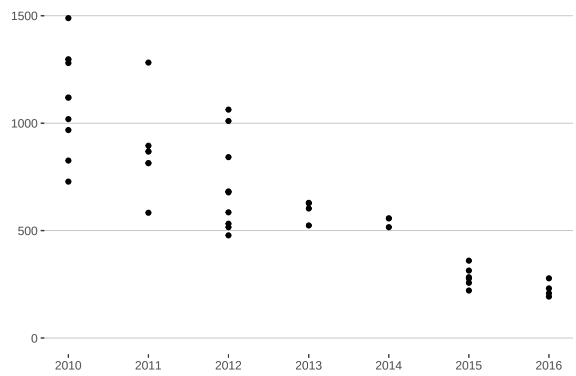

Figure 1: Lithium-ion cell price estimates (USD per kWh)

Different estimates of lithium-ion cell prices. Source: Hsieh et al. (2019)

2.1 Industry description

The market for electric vehicles. After having been dormant for more than 100 years, electric vehicle technology returned to prominence in the late 1990s. Both the Honda Insight and the Toyota Prius used a hybrid engine that combined fuel and electric powertrains. However, it was not possible to plug this electric engine into an external source. Over the past decades, two new technologies have emerged. One is the plug-in hybrid electric vehicle (PHEV), which combines a fuel engine with an electric battery pack that can be plugged into an external power source. The other is a pure battery electric vehicle (BEV), whose powertrain unit consists only of a battery pack (throughout the remainder of the text, "BEV" is used synonymously with "battery electric vehicle", "PHEV" is used synonymously with "plug-in hybrid electric vehicle" and "EV" refers to both "BEV" and "PHEV"). Electric vehicles have been singled out by policymakers and firms alike as key technologies to decarbonize the transportation sector in pursuit of containing the rise of global temperatures to below $1.5°$C. To buttress diffusion, governments around the world have introduced subsidies and tax incentives for electric vehicles. The scope and design of these subsidies vary considerably across and sometimes even within countries. Some countries use flat subsidies, and others make subsidies dependent on characteristics such as the driving range or battery size.[2]. Global government spending on EVs increased substantially from $1 billion in 2012 to $15 billion in 2018.

Another feature of the electric vehicle market is the rapid decrease in the cost of lithium-ion cells (LICs). Numerous LICs make up the battery pack of an electric vehicle. This battery pack propels the car, and its size is the most important determinant of the driving range. Figure 1 shows different approximations of the evolution of lithium-ion cell prices. Although there is considerable variation in the estimates, there is a clear downward trend. This trend suggests that providing a higher driving range has become considerably cheaper over the past decade.

Significant barriers to the mass adoption of electric vehicles exist: EVs tend to be more expensive and have a shorter driving range than combustion engine cars. In consumer surveys,

[2]For detailed overviews, see Yang, Slowik, Lutsey, and Searle (2016) and Rokadiya and Yang (2019).

the high cost and small range of EVs repeatedly show up as the most critical determinants of whether to purchase an electric vehicle, together with the charging station network density (see, for instance, Schoettle and Sivak 2018; Carley, Krause, Lane, and Graham 2013; Rezvani, Jansson, and Bodin 2015). Both a low range and low charging station network density contribute to a low perceived quality of EVs and low autonomy.

Electric vehicles in Germany. The automobile sector is a key industry in Germany, accounting for 9.8% of gross value added and employing approximately 880,000 people, with another 900,000 jobs heavily depending on the sector, for a combined share of 7.2% of total employment.[3] Germany is home to three of the largest 15 car manufacturers in the world as measured in sales and was ranked fourth in the world in terms of motor vehicle production during the sample period.

Over the past decade, the German government has implemented measures to boost sales of electric vehicles. One such measure was the Government Program for Electric Mobility of 2016. Part of this program was a support scheme that offered a €2,000 subsidy for the purchase of battery electric vehicles and a €1,500 subsidy for the purchase of plug-in hybrid electric vehicles. The car had to have a list price below €60,000 to be eligible for the subsidy.[4] In total, the government provided €600 million in subsidies.[5] The program also provided a total of €200 million in funding for new charging stations, starting in 2017. The amount of the subsidy depended on the type of charging stations. Charging stations with a charging capacity of up to 22 kW (also called Level 2 chargers) received up to €3,000 towards installation and €5,000 towards connection to the electricity grid (if the charging point was connected to the medium-voltage grid, the connection subsidy was up to €50,000). Level 2 chargers are the dominant type of charger in my sample, representing almost 87% of all public chargers at the end of 2021. Table 9 in Appendix A gives an overview of the number and type of chargers available by year.

The plan reinforced the government's goal to have 1 million electric cars on the streets by 2020 and 6 million by 2030.[6] The budget for the EV purchase subsidies was forecast to be sufficient to give subsidies until 2019. However, by June 2017, only approximately 5% of the total budget had been used, and in 2018, the market share of battery electric vehicles was only 1.2%, with approximately 34,000 annual car sales. These lackluster sales numbers led

[3] `https://www.iwkoeln.de/en/studies/iw-reports/beitrag/thomas-puls-manuel-fritsch-the-importance-of-the-automotive-industry-for-germany.html`

[4] Such maximum price provisions are quite common and are or were used in France, the UK, and the Netherlands, for instance (see `http://tinyurl.com/ydmnyc82`, `http://tinyurl.com/y7a57zxm`, and `http://tinyurl.com/4jbyudxj`). In the structural model, I ignore this maximum price. Only two models cross it in some of the counterfactuals, which does not affect the main results of the paper.

[5] Car manufacturers pledged to match the government subsidy by granting a rebate equal to the amount of the subsidy. The program also provided various tax benefits for buying, using, and charging electric vehicles. See also `https://www.bmwi.de/Redaktion/EN/Artikel/Industry/regulatory-environment-and-incentives-for-using-electric-vehicles.html`

[6] `https://www.bmwi.de/Redaktion/DE/Downloads/P-R/regierungsprogramm-elektromobilitaet-mai-2011.pdf?__blob=publicationFile&v=6`

the government to increase the subsidy scheme's scope as part of a federal climate protection act in 2019. This act increased the government subsidy for battery electric vehicles to up to € 3,000, depending on the list price. The act also increased tax incentives for electric vehicles and introduced a price of € 10 per ton on CO_2 from 2021 onward, which has since increased to € 30 per ton on CO_2. In total, the government pledged € 9 billion for subsidies, tax reductions, and charging infrastructure. Finally, in response to the economic crisis caused by the COVID-19 pandemic, the government doubled the subsidies to € 6,000.

At the same time, individual federal states also introduced support for e-mobility. In particular, many states introduced support schemes for charging stations. These support schemes are often similar in design to that implemented by the federal government. However, the state schemes differ both in the size of financial incentives and their introduction date.

The market for public chargers is very fragmented, with the 5 largest firms combined owning only 16.8% of charging points in 2021, and the 10 largest firms owning 26% of charging points in 2021. Overall, some 3,300 firms and municipalities own charging points. Concentration is somewhat higher at the state level, as the largest firms tend to focus on specific areas of Germany. Until the end of 2018, car makers were practically absent from the charging station side.[7] As of 2021, only Volkswagen had started to build some charging stations, albeit at a very low level and mostly around their factories. Another carmaker initiative is Ionity, a firm jointly owned by several carmakers (VW, BMW, Daimler, Ford) with the goal of deploying a network of chargers along European freeways. However, at the end of 2021, Ionity had provided only 0.77% of all charging points.

A distinguishing feature of EVs compared to conventional cars is the possibility to charge the battery at home. Studies suggest that 49%-80% of charging in Germany occurs at home and 8%-25% at public chargers (see for instance Preuß, Kunze, Zwirnmann, Meier, Plötz, and Wietschel, 2021). These figures suggest that public chargers satisfy an important amount of demand for charging. Moreover, public chargers are crucial in incentivizing EV uptake among consumers who do not have access to home charging. In that sense, more public charging station entry can induce latent demand of consumers who have not previously considered buying an EV.

2.2 Data

I build a comprehensive data set of new car purchases in Germany from 2012 to 2018 and of charging station entry in Germany from 2012 to 2021. I do so by combining several data sources.

Car registrations. I use publicly available data from the German Federal Motor Transport

[7] The obvious exception is Tesla, which has rolled out its own network. However, throughout the sample period, Tesla's chargers were not available to EVs of other manufacturers, which is why Tesla chargers are not included in the analysis.

Authority (KBA). This data set contains yearly new registrations at the state level for every car model.[8] A firm-and-trim identifier ("HSN/TSN") defined at a very granular level identifies a model. It differs by car class, body type, engine type, kilowatts, weight, and the number of doors. I follow the previous literature on demand estimation for car markets in treating new registrations as sales.

Car prices and characteristics. I scraped data on car prices and characteristics from the website of the General German Automobile Club (ADAC), giving me a comprehensive data set containing a wide range of car characteristics. These characteristics include the driving range of cars. The data also include the list price of cars, which I use in the estimation as the transaction price, again following the literature on demand estimation for car markets. The ADAC data also contain the HSN/TSN identifier, allowing me to match the two data sets relatively easily, except for some observations requiring manual matching.

EV charging stations. I obtain the number of charging stations for electric car batteries from a publicly available data set listing all public charging stations from the Federal Network Agency (BNetzA).[9] The data set contains each station's opening date and its location. The data also gives information on the type of charging station (capacity in kW and the type of grid connection).

Suppliers. I use data on manufacturer-supplier links from MarkLines. This data allows me to identify the country where a given model is produced and the identity and location of every EV's battery supplier. The MarkLines data also contains model-level sales in every European country.

Further data. I use data from the German Socio-Economic Panel (SOEP) to build income distributions at the state-year level. To do so, I fit the mean and variance of a log-normal distribution using the observed household income draws of the SOEP. Additional data on population comes from the Federal Statistics Office, and CPI data are from Federal Reserve Economic Data. To have a measure of usage cost of different cars, I build a measure of fuel cost in €/100 km using yearly average gas price data from ADAC and electricity cost data from the German Economics Ministry. In addition, I also collect information on the number of gas stations and their prices using data published by tankerkoenig.de. This data is only available from the end of 2014 onward, which is why I only use it on the charging entry side and not in the demand estimation.

The resulting data set defines a product at a very detailed level. A trade-off exists between having a very granular product definition and a more aggregated definition for tractability. In my

[8] Germany consists of 16 states ("Bundesländer"). Three of these states (Berlin, Hamburg, and Bremen) are "city-states" whose boundaries coincide with the cities themselves. The other 13 states are larger in area, ranging from approximately the land area of Rhode Island to approximately that of South Carolina. The population of the 16 states ranges from approximately 680,000 (roughly comparable to that of Alaska) to approximately 18 million (roughly comparable to that of New York state).

[9] In the remainder of the paper, I will use "public charging stations" and "charging stations" interchangeably.

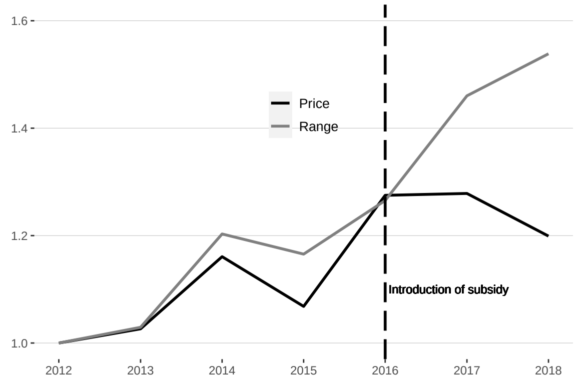

Figure 2: Evolution of price and range of battery electric vehicles

This figure shows the average price and range per year relative to 2012 values that are normalized to 1.

final data set, I define a product at the firm/model/engine type level, with the possible engine types being combustion (ICE), plug-in hybrid (PHEV), or battery electric (BEV) engines (e.g., VW Golf ICE vs. Renault Zoe BEV). I use the price and characteristics of the most frequently sold variant at the national level. I reduce the size of the data further by leaving out firms and models with low sales. In addition, I delete models with a nominal list price above € 100,000. I set the size of the potential market equal to the number of households in a given state in a given year. In total, the data consists of 28,288 year-state-product observations. Detailed summary statistics can be found in Table 8 of Appendix A.

Figure 2 shows how the average price and range of battery electric vehicles developed during the sample period. Prices slightly increased, and the range rose by almost 60%. Both the entry of new cars with higher range and range upgrades of existing cars contributed to this increase in range (see also Figures 5 and 6 in Appendix B). It is unclear from Figure 2 to what extent falling LIC prices and subsidies drove these trends. The structural model will allow me to disentangle these effects.

2.3 Reduced-form evidence

There are several reasons suggesting that firms adjust range frequently and in response to policy changes in the German market. First, range is relatively easy to adjust in the short run compared to attributes such as the size of the car, which is typically fixed over a 7 to 8 year horizon. Figure 6 in Appendix B shows the evolution of range for selected models in my data. We can see that range is adjusted frequently by firms. I also report other attributes. The footprint, height, and horsepower of BEVs stayed constant for most models or changed at the most once. Quotes from industry executives and news articles on EVs corroborate this. In a 2016 investor call, in response to a question pointing to BMW only introducing their next new EV in 2020, then-CEO Harald Krüger noted “What we do in between, (...), we’re increasing the battery capacity of the i3 which will have then 50% more model range (...) and we’re still working in the future on more."[10] A news article from 2017 talking about a range increase for Volkswagen's e-Golf describes the source of the range update: "Improved battery cells will allow Volkswagen to fit more powerful batteries into the same physical space occupied by the current batteries."[11]

Second, manufacturers tailor EVs to specific markets. In 2021, then Volkswagen CEO Herbert Diess announced, "Volkswagen is bringing a wide range of highly attractive BEVs tailored to the U.S. market (...)".[12] In an investor call in 2019, VW Director of Group Sales Christian Dahlheim noted "(...) that most models are country specific."[13] In 2018, the Mitsubishi Outlander received a range upgrade in Europe, which was introduced in the US only 3 years later.[14]. While this tailoring seems to be mostly done at the European level, it is reasonable to expect that the German market plays a crucial role in tailoring cars to the European market: Throughout the sample, Germany was the largest market for cars in Europe and the fourth largest worldwide in terms of new car sales. Table 14 in Appendix A compares sales numbers of EVs across European countries in 2018. We can see that for most models, Germany was one of the three most important markets and accounted for a substantial share of European sales. Overall, these reasons motivate my choice that firms strategically set price and range in response to German demand and policies.

To get a better idea of whether prices and range adjust to subsidies, I present some reduced-form evidence. For this, I extend the data set of BEV prices and characteristics to the end of 2020. Doing so has two advantages: First, it provides me with 2 more years of data in which more BEVs entered or were upgraded. Second, it allows me to exploit an increase in the purchase subsidy in late 2019. The subsidy increased to €3,000 for BEVs with a list price of less than €40,000 and to €2,500 for BEVs with a list price between €40,000 and €65,000. I regress the driving range and price of all BEVs in the sample on the amount of the subsidy the BEV qualifies for, car characteristics, and different levels of fixed effects.

The results are in Table 1. I estimate a negative impact of the subsidy on both price and range. The results are relatively robust across the different specifications for both price and range. They suggest two effects: First, price pass-through seems to be more than 100%. The results in the last column suggest that a €1,000 subsidy increase is associated with about a €5,000 price reduction. Second, firms seem to reduce the driving range of cars when subsidies increase. The last column suggests that a €1,000 subsidy increase is associated with an almost 65km decrease in the range. This evidence is in line with findings in other countries. Jia Barwick et al. (2023) show that in response to a range-based subsidy, firms adjusted their driving range by bunching around cut-offs present in the Chinese subsidy scheme at the time.

Caution should be taken with claiming causality here. These subsidies were introduced at

[10] Bayerische Motoren Werke AG (BAMXY) on Q1 2016 Results - Earnings Call Transcript

[11] https://www.motortrend.com/news/volkswagen-e-golf-to-get-30-percent-driving-range-improvement/

[12] Volkswagen Media information No. 123/2021

[13] Volkswagen AG ADR (VWAGY) Management on Q3 2019 Results - Earnings Call Transcript

[14] https://insideevs.com/news/394837/mitsubishi-expected-to-update-outlander-phev-us/

a time when battery costs rapidly declined and subsidized cars competed with non-subsidized cars, making it difficult to define a proper control group. Moreover, the public charging network expanded rapidly over the time period, which likely affected and interacted with firm strategies. Disentangling the effect of subsidies from these other factors requires a structural model.

Table 1: Reduced-form results

Dependent Variable:	Range				
Subsidy	-28.96	-45.85	-44.30***	-59.86**	-64.63**
	(18.84)	(25.05)	(11.99)	(24.41)	(26.06)
R^2	0.82307	0.95274	0.83272	0.95581	0.97114
Dependent Variable:	Price				
Subsidy	-4.382	-1.111	-4.798**	-4.432**	-5.237***
	(2.785)	(3.345)	(1.833)	(1.344)	(1.309)
R^2	0.96047	0.98426	0.96110	0.98694	0.99223
Further controls			Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes		Yes		
Model FE		Yes		Yes	
Body FE	Yes	Yes	Yes	Yes	
Class FE	Yes	Yes	Yes	Yes	
Product FE					Yes
Observations	152	152	152	152	152

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Observation is a model-year. There are 45 models in the data set, and the data runs from 2012-2020. I only use data on BEVs sold in Germany.

3 Empirical Model

This section introduces a structural model of demand and supply for new cars and entry of public electric charging stations. I assume that each period starts with a given number of circulating EVs. The game then proceeds with car makers choosing the price and range. Consumers then make their purchase decisions and charging stations enter. The main implication of this timing assumption is that it makes the indirect network effects explicit in the price and range decisions of electric car producers.[15]

The model is static. Carmakers tend to update their models every 7-8 years. I do not have the data necessary to look at these kinds of long-term decisions. Likewise, consumers tend to use a vehicle for 5-6 years. Hence, estimating a dynamic model requires a very long panel. Finally, given the importance of cars for many consumers, it is unlikely that consumers defer car purchases in expectation of future events but rather choose a different option. My model still captures the main channel through which the chicken-and-egg problem manifests itself on the

[15] An alternative way of modeling this game would be to assume car makers and charging stations move simultaneously. In such a set-up, the indirect network effects are no longer explicit in the price and range choices but will still be present when performing counterfactual analyses. Appendix D shows the results from such a model.

demand side since I model substitution between EVs and other cars. Doing so requires endogenous price and range choices to be taken into account, as well as their interaction with indirect network effects, which is already challenging. Adding dynamics on top of these challenges is beyond the scope of this paper.

3.1 Car demand

A state m observed in year t defines a market. There are $\mathcal{M}_{mt}$ consumers in each market mt. Each consumer i chooses one option j, which is either the outside option $j = 0$ or one of the $j = 1, \ldots, J$ differentiated products. Choosing the outside option means that the consumer buys a used car or does not buy a car at all. Choosing one of the "inside" products means buying a new car. The utility that consumer i enjoys from purchasing one of the products $j = 1, \ldots, J$ is

$$\begin{aligned} u_{ijmt} = & \underbrace{\beta_i^b BEV_j + \beta_i^p PHEV_j + \beta_i^r r_{jt} + \beta^d log(d_{jmt})}_{\text{only EVs}} \\ & \underbrace{-\alpha \frac{p_{jt}}{y_{imt}} + x_{jmt}\beta_i^x + \xi_{jmt} + \varepsilon_{ijmt}}_{\text{all cars}}, \end{aligned} \tag{1}$$

where BEV_j ($PHEV_j$) is an indicator equal to one if the product is a BEV (PHEV), r_{jt} is the range of product j, d_{jmt} is the number of charging stations available in state m in year t, p_{jt} is its price, y_{imt} is the income of consumer i, and x_{jmt} is a vector of observed product characteristics. ξ_{jmt} is an unobserved characteristic of product j in market mt, and ε_{ijmt} is a consumer-specific unobserved taste shock assumed to be an i.i.d. type-I extreme value. The parameter vector β_i^x consists of mean tastes for characteristics and, for some characteristics, random coefficients capturing unobserved heterogeneity in the valuation of product characteristics. For a characteristic k, we have $\beta_i^k = \beta^k + \sigma^k \nu_i^k$ with ν_i^k drawn randomly from a standard normal distribution and σ^k being the standard deviation of preferences. The parameter β^r captures preferences for range, β^d captures preferences for the size of the charging network, and α captures price sensitivity. I assume that consumers care only about the driving range of battery and plug-in hybrid electric vehicles and not about the driving range of combustion engine cars. In the model, this translates into setting $r_{jt} = 0$ for products with a combustion engine. Likewise, $log(d_{jmt})$ is zero if j is a combustion car.[16] The utility from purchasing the outside option is normalized to $u_{i0mt} = \varepsilon_{i0mt}$.

Consumer i in market mt chooses alternative $j = 0, \ldots J$ that maximizes her utility. Each

[16] Evidence from numerous consumer surveys motivate these assumptions. See, for instance, `https://www.compromisorse.com/upload/noticias/002/2794/accentureelectricvehicle.pdf`. Specifically for Germany, see `https://www.aral.de/content/dam/aral/business-sites/de/global/retail/presse/broschueren/aral-studie-trends-beim-autokauf-2019.pdf`. The latter study (in German) also shows that consumers do not take range into account when deciding on the purchase of a combustion engine car.

consumer is characterized by her income y_i and her vector of idiosyncratic preferences ν_i. Income y_i follows a log-normal distribution whose parameters I estimate based on draws from the observed income distribution. Integrating over the individual-specific valuations for characteristics gives the choice probabilities:

$$s_{jmt}(p,r,d,x,\xi;\sigma) = \\ \int\int \frac{\exp(\delta_{jmt} + \mu_{ijmt}(p_{jt}, r_{jt}, d_{jmt}, x_{jmt}, \xi_{jmt};\sigma))}{1+\sum_{k=1}^{J}\exp(\delta_{kmt} + \mu_{ikmt}(p_{kt}, r_{kt}, d_{kmt}, x_{kmt}, \xi_{kmt};\sigma))} dF(\nu)dG(y),$$

where $F(\cdot)$ is the joint CDF of the unobserved taste shocks and $G(\cdot)$ is the distribution of income. Further, δ_{jmt} is the mean utility incorporating all terms from (1) that do not vary across individuals, and $\mu_{ijmt} = -\alpha\frac{p_{jt}}{y_{imt}} + \sum_k \sigma^k \nu_i^k x_{jmt}^k$ captures individual deviations from the mean utility. Finally, defining the observed market share as $s_{jmt} = \frac{q_{jmt}}{\mathcal{M}_{mt}}$, with q_{jmt} being the observed quantity of product j in market mt, in addition to stacking observed and predicted market shares into a vector, we obtain the system of equations $s_{mt} = s_{mt}(p,r,d,x,\xi;\sigma)$ for each market mt.

3.2 Car supply

I model the profit-maximizing price and range decisions of F multi-product firms for each year t. I assume the product portfolio of firms to be given and that firms have already chosen all product characteristics except for the range of BEVs.[17] Firms then maximize profits by setting the price of all products in their portfolio as well as setting the range of their BEVs at the national level. Firms take into account indirect network effects, which accrue for both BEVs and PHEVs. I will defer the analysis of the role indirect network effects play in firm decisions until after the charging station entry side has been introduced.

The profit in year t is then the weighted sum of profits from each state m, and firm f's profit maximization problem can be written as follows:

$$\max_{p,r} \pi_{ft} \equiv \sum_{j\in\mathcal{J}_{ft}} \big(p_{jt} + \lambda_{jt} - mc_{jt}(r_{jt}, w_{jt};\theta_s)\big) s_{jmt}(p,r,d,x,\xi;\sigma)\mathcal{M}_{mt}, \tag{2}$$

where $\mathcal{J}_{ft}$ is the product portfolio of firm f, λ_{jt} is a subsidy, $mc(\cdot)$ is the marginal cost of product j, w_j is a vector of observed cost-shifters and θ_s is a vector of parameters entering the marginal cost function. The subsidy can be made dependent on attributes such as an EV's range in counterfactuals. Consumer prices are given by p_{jt} and firm prices by $p_{jt} + \lambda_{jt}$.[18] The

[17] I do not model range decisions of PHEVs because the technology is different and range levels have stayed flat over the sample period. In addition, Grigolon, Park, and Remmy (2024) find that PHEVs are used mainly in fuel mode.

[18] I also account for a 19% value added tax (vat) levied on cars in Germany, which means that firm prices are given by $\tilde{p}_{jt} = p_{jt}/(1+\text{vat}) + \lambda_{jt}$. I ignore vat in the exposition for notational convenience.

first-order conditions with respect to price and range are then given by

$$\frac{\partial \pi_{ft}}{\partial p_{jt}} = \sum_m \phi_{mt} \Big\{ s_{jmt} + \sum_{k \in \mathcal{J}_{ft}} \big(p_{kt} + \lambda_{kt} - mc_{kt} \big) \frac{\partial s_{kmt}}{\partial p_{jt}} \Big\} = 0 \tag{3}$$

$$\frac{\partial \pi_{ft}}{\partial r_{jt}} = \sum_m \phi_{mt} \Big\{ - \frac{\partial mc_{jt}}{\partial r_{jt}} s_{jmt} + \sum_{k \in \mathcal{J}_{ft}} \big(p_{kt} + \lambda_{kt} - mc_{kt} \big) \frac{\partial s_{kmt}}{\partial r_{jt}} \Big\} = 0, \tag{4}$$

where $\phi_{mt} = \frac{\mathcal{M}_{mt}}{\sum_{m'} \mathcal{M}_{m't}}$ is the weight of state m. Equation (3) is the usual first–order condition with respect to price, where firm f trades off increasing the markup on product j by increasing the price against losing market share due to this price increase, adjusted by the effect of changing j's price on the demand of other products that firm f offers.

When choosing the range, firm f trades off the decrease in the markup from providing more range (intensive margin) against the higher demand arising from this range increase (extensive/switching margin) and the cannibalization effect on the other products in firm f's portfolio. Loosely speaking, equilibrium range decreases with a higher marginal cost of range (which squeezes the markup) and increases with a higher demand semi-elasticity with respect to range (which increases the extensive margin).[19]

Appendix E further gives details on the supply model.

Marginal cost specification

I specify a marginal cost function that is log-linear. For product j, it is given by

$$\log(mc_{jt}(q_{jt}, w_{jt}; \theta_s)) = \underbrace{w_{jt}\psi + \omega_{jt}}_{\substack{\text{baseline} \\ \text{marginal cost}}} + \underbrace{(\gamma_0 + \gamma_1 t + \eta_{jt}) r_{jt}}_{\substack{\text{marginal cost of} \\ \text{providing range}}}, \tag{5}$$

where w_{jt} is a vector of observed cost-shifters, ω_{jt} is a cost shock observed by firms but unobserved by the researcher, t is a linear time trend, η_{jt} is a range-specific marginal cost shock observed by firms but unobserved by the researcher, and $\theta_s \equiv (\psi, \gamma_0, \gamma_1)$ is a vector of parameters to be estimated. Note that the second part of (5) is zero for products that are not battery electric vehicles since I do not model their range choices. In the case of BEVs, I assume that the marginal cost of providing range depends on an intercept term, a linear time trend allowing for less costly range provision over time, and an unobserved, product-specific component. The exponential nature of fixed costs is in line with the technology facing firms: Increasing range may be achieved by increasing the size of the battery. A kilometer of range becomes more costly at higher range levels. One reason is that the car's dimensions restrict the size of the battery. Additionally, other ways of increasing range, such as achieving a higher energy density of batteries, may also be constrained by technological factors and make provision of range

[19] I do not allow for fixed costs in adjusting range because I model short-term adjustments once the other attributes have been chosen, such as using more battery cells per car or using denser, more expensive cells. These adjustments will mainly be reflected in marginal cost,

costlier at higher range levels.

3.3 Charging station entry

The exposition of this section closely follows Springel (2021). For more details, refer to her exposition of the model. The main difference between her framework and mine is that I model a car supply side with endogenous price and range choices in which I explicitly take into account the effect of indirect network effects on price and range decisions.

Let h be one of d_{mt} stations in state m in year t. A station h enjoys per-consumer profits

$$\mathcal{D}_{hmt}(p^e_{hmt}, p^e_{-hmt}, d_{mt})(p^e_{hmt} - c^e_{hmt}),$$

where $\mathcal{D}_{hmt}$ is the per-consumer demand for station h, p^e_{hmt} is the price station h charges and c^e_{hmt} is the marginal cost of station h.[20] I assume stations have perfect foresight. Following Bresnahan and Reiss (1991); Gandal, Kende, and Rob (2000), and Springel (2021), I assume that i) per-consumer demand functions are symmetric, ii) each charging point faces the same marginal and sunk entry costs and iii) each station h gains an equal share of the market.[21] Under these assumptions, an equilibrium exists in which each station charges the same price and we can express the period–t profits upon entry

$$\pi_{mt} = Q^{EV}_{mt} \underbrace{\frac{\mathcal{D}(p^e(d_{mt}))(p^e - c^e)}{d_{mt}}}_{\equiv \vartheta(d_{mt})}, \tag{6}$$

where Q^{EV} denotes the stock of electric vehicles circulating in state m in year t.[22] Following the previous literature, I assume the equilibrium price to be a decreasing function of the number of stations. A station deciding to enter in year t incurs a sunk cost of entry F_{mt} and earns a sequence of yearly profits. In a free-entry equilibrium, a firm must be indifferent between entering and start earning the profit sequence in t and entering in $t+1$, which implies

$$\begin{aligned} &- F_{mt} + \rho\pi_{m,t+1} + \rho^2\pi_{m,t+2} + ... \\ &= -\rho F_{m,t+1} + \rho^2\pi_{m,t+2} + \rho^3\pi_{m,t+3} + ..., \end{aligned} \tag{7}$$

with ρ the discount rate. Combining equations (6) and (7) and taking the natural logarithm

[20] I add the superscript e to avoid confusion with car prices and marginal costs.

[21] Although different types of charging stations do exist (slow vs. fast), the vast majority of charging stations built over the sample period were relatively similar in their charging speed.

[22] Since I only have information on the BEV stock, I set the initial EV stock equal to the initial BEV stock on January 1 2012. I calculate the stock in year t as $stock_t = newsales_t + stock_{t-1} + scrappage_{t-1}$. I only have information on BEV scrappage, which was around 10% of the stock every year. Accordingly, I assume total EV scrappage to be 10% each year. The results are robust to assuming no scrappage as well as assuming a larger initial stock to account for PHEVs bought before 2012.

yields the following equation:

$$\log(\vartheta(d_{mt})) = -\log(\rho) - \log(Q_{mt}^{EV}) + \log\left(F_{mt} - \rho F_{m,t+1}\right) \tag{8}$$

Letting $\vartheta(d_{mt}) = (\kappa d_{mt})^{\iota}$ and assuming that $\log\left(F_{mt} - \rho F_{m,t+1}\right)$ is a linear function of national and state charging station subsidies, a linear time trend and state demographics (respectively fixed effects), I obtain the following estimating equation:

$$\begin{aligned} log(d_{mt}) = \upsilon_1 + \upsilon_2 \log(Q_{mt}^{EV}) + \upsilon_3 \text{National Subsidies}_{mt} + \upsilon_4 \text{State Subsidies}_{mt} \\ + \upsilon_5 \varrho_t + x_{mt}^{c'} \boldsymbol{\upsilon}_6 + \epsilon_{ct} \end{aligned} \tag{9}$$

3.4 Firm choices and indirect network effects

The assumed timing of the game modifies the first–order conditions of firms. In particular, market share derivatives with respect to price and range change as firms anticipate the effect of their actions on the charging station side. Analyzing the role of indirect network effects in firms' price and range choices requires some further notation. Let the partial derivative of model k's share with respect to model j's price absent network effects (i.e., $\beta^n = 0$ or $\lambda_1 = 0$) be given by

$$\eta_{kj} \equiv \begin{cases} \int\int -\frac{\alpha}{y_i} s_{ij}(1 - s_{ij}) dF(\nu) dG(y) \text{ if } k = j \\ \int\int -\frac{\alpha}{y_i} s_{ij} s_{ik} dF(\nu) dG(y) \text{ otherwise} \end{cases}$$

and the station semi-elasticity absent indirect network effects (i.e., $\upsilon_2 = 0$) be given by

$$\gamma_j \equiv \beta^d \int\int s_j(1 - s_j) dF(\nu) dG(y).$$

Let $\mathcal{J}^{EV}$ denote the set of EVs present in the market. Note that I suppress the dependence of market shares on attributes, prices, and parameters as well as market- and time subscripts for notational convenience. From Springel (2021), we know that we can then express the partial derivative of the EV market share (denoted s^{EV}) with respect to the price of product j as

$$\frac{\partial s^{EV}}{\partial p_j} = \sum_{k \in \mathcal{J}^{EV}} \eta_{kj} + \frac{\upsilon_2}{s^{EV}} \frac{\partial s^{EV}}{\partial p_j} \sum_{k \in \mathcal{J}^{EV}} \gamma_k = \frac{\sum_{k \in \mathcal{J}^{EV}} \eta_{kj}}{1 - \frac{\upsilon_2}{s^{EV}} \sum_{k \in \mathcal{J}^{EV}} \gamma_k}$$

The partial derivative of product j's share with respect to its price is then given by

$$\begin{aligned} \frac{\partial s_j}{\partial p_j} &= \eta_{jj} + \frac{\partial s_j}{\partial \log d} \frac{\partial \log d}{\partial Q^{EV}} \frac{\partial Q^{EV}}{\partial p_j} \\ &= \eta_{jj} + \upsilon_2 \gamma_j \frac{\sum_{k \in \mathcal{J}^{EV}} \eta_{kj}}{s^{EV} - \upsilon_2 \sum_{k \in \mathcal{J}^{EV}} \gamma_k}, \end{aligned}$$

where d denotes the number of charging stations.[23] Assuming that $s^{EV} - \upsilon_2 \sum_k \gamma_k > 0$ [24] we can directly see two opposing forces acting on the augmented partial derivative: On the one hand, the network effect directly related to the own-product market share makes $\frac{\partial s_j}{\partial p_j}$ more negative, because raising the price reduces sales of the own product, resulting in lower charging stations, which in turn lowers sales further. This gives the firm fewer incentives to increase prices. On the other hand, the network effect related to rival product market shares makes $\frac{\partial s_j}{\partial p_j}$ less negative, because raising the price will increase rival-product sales, which increases the number of charging stations and in turn leads to higher own sales. This effect gives the firm more incentives to increase prices. Since we would expect $\eta_{jj} > \sum_{k \neq j} \eta_{kj}$, indirect network effects will make $\frac{\partial s_j}{\partial p_j}$ and as a consequence also the own-price elasticity more negative.

We can similarly derive the cross-price derivatives, which become

$$\frac{\partial s_j}{\partial p_k} = \eta_{jk} + \upsilon_2 \gamma_j \frac{\sum_{l \in \mathcal{J}^{EV}} \eta_{lk}}{s^{EV} - \upsilon_2 \sum_{l \in \mathcal{J}^{EV}} \gamma_l} \tag{10}$$

Since cars are substitutes, we have $\eta_{jk} > 0$. If $\eta_{jj} > \sum_{k \neq j} \eta_{kj}$ and $\frac{\partial s_j}{\partial p_j}$, cross-price derivatives will become less positive or even negative, in which case EVs will act as complements.

Analogously, we can derive the own-and cross-range derivatives. The effects will mirror the analysis of price derivatives above. Let the partial derivative of model k's share with respect to model j's range absent network effects be given by

$$\eta^r_{kj} \equiv \begin{cases} \int \int \beta^r_i s_{ij}(1 - s_{ij}) dF(\nu) dG(y) \text{ if } k = j \\ \int \int \beta^r_i s_{ij} s_{ik} dF(\nu) dG(y) \text{ otherwise} \end{cases}$$

The partial derivative of product j's share with respect to product k's range is then

$$\begin{aligned} \frac{\partial s_j}{\partial r_j} &= \eta^r_{jj} + \upsilon_2 \gamma_j \frac{\sum_{k \in \mathcal{J}^{EV}} \eta^r_{kj}}{s^{EV} - \upsilon_2 \sum_{k \in \mathcal{J}^{EV}} \gamma_k} \quad \text{if } k = j, \\ \frac{\partial s_j}{\partial r_k} &= \eta^r_{jk} + \upsilon_2 \gamma_j \frac{\sum_{l \in \mathcal{J}^{EV}} \eta^r_{lk}}{s^{EV} - \upsilon_2 \sum_{l \in \mathcal{J}^{EV}} \gamma_l} \quad \text{if } k \neq j \end{aligned}$$

Since increasing the range increases the own-product market share, indirect network effects will make the own-range derivative larger. Since increasing the range absent indirect network effects decreases rival EV shares, indirect network effects will become less negative or even positive, in which case EVs will act as complements.

[23] Note that I shut down possible dynamic considerations here: Setting a lower price today may lead to more charging stations in the next period since the stock of EVs will be larger. By shutting down this demand-enhancing effect, I may underestimate the incentives to charge a lower price, so the effects found can be thought of as a lower bound. Writing down the full dynamic pricing problem in a multi-product oligopoly setting with complementary charging station entry is beyond the scope of this paper and left to future research.

[24] This will hold if the size of the indirect network effects is "small enough" relative to the size of the EV market.

These modified first order conditions affect price and range choices: Equations (11) and (12) pin down optimal price and range levels in the presence of subsidies. The subsidy will alter both price and range since both are a function of the subsidy in equilibrium. The optimal price and range levels are also a function of the indirect network effects as they depend on the (modified) price and range derivatives. The matrices Δ_p and Δ_r^B hold these price- and range derivatives, respectively.

4 Estimation

4.1 Instrumental variables

Estimation of the demand side parameters suffers from the well-known endogeneity issue related to price and in this case also to range: As the demand- and supply-side shocks are realized before the price and range choices, price and range may be correlated with these unobservables. The utility function also includes the number of charging stations available to electric vehicles. The charging station network is itself likely to depend on the electric vehicle base, creating an endogeneity issue (Pavan, 2017; Springel, 2021; Li, 2023). Instruments are needed to account for this endogeneity issue. At the same time, instruments also help identify the random coefficients, thus serving a dual role. Recent literature has pointed out that the classic BLP instruments, consisting of simple sums of product characteristics, tend to perform rather poorly (Reynaert and Verboven, 2014; Gandhi and Houde, 2019). This literature suggests finding approximations to optimal instruments as in Chamberlain (1987). In my estimation, I use differentiation IVs as introduced by Gandhi and Houde (2019). The idea is to describe the relative position of each product in the characteristics space. I build three variants of differentiation IVs: a local variant that counts products close in characteristic space and a quadratic variant that sums squared differences between product characteristics:

$$Z_{jt}^{k,\text{local}} = \sum_{l \in \mathcal{C} \setminus \{j\}} \mathbf{1}\{|\mathcal{H}_{k,jlt}| < sd(\mathcal{H}_k)\}, \quad Z_{jt}^{k,\text{quadratic}} = \sum_{l \in \mathcal{C} \setminus \{j\}} \mathcal{H}_{k,jlt}^2,$$

where $|\mathcal{H}_{k,jlt}|$ is the absolute value of the difference between products j and l in characteristic k, $sd(\mathcal{H}_k)$ is the standard deviation of characteristic k across markets, and $\mathcal{C}$ is the set of products considered. I build a discrete variant for discrete variables that counts the number of products with the same value for the characteristic:

$$Z_{jt}^{k,\text{discrete}} = \sum_{l \in \mathcal{C} \setminus \{j\}} \mathbf{1}\{|\mathcal{H}_{k,jlt}| = 0\}$$

I build four kinds of instruments of each variant: one considering own-firm products, one considering rival-firm products, one considering own-firm products of the same engine type

(BEV, PHEV, or ICE) and one considering rival-firm products of the same engine type.

I build the local and quadratic variants for all continuous characteristics and the discrete variant for all discrete characteristics. I also create local and quadratic variants for a price index, obtained from regressing the observed price on demand- and cost-shifters. The range of BEVs is endogenous, but I assume that the range of PHEVs is not. This is why I build the local and quadratic variants for the range of plug-in hybrid vehicles. I also build the local and quadratic variants for battery efficiency (measured in kWh/100 km), which I assume to be exogenous. I use a subset of all the instruments that I create.

Car demand: price I exploit data on manufacturer-supplier links that allows me to identify a specific model's country of production. Following Grieco, Murry, and Yurukoglu (2023), I use the PPP-adjusted exchange rate between Germany and the country of production, as provided in the Penn World Tables. This shifter accounts for cost changes via wage changes and via nominal exchange rate changes. I also use an index for steel prices (obtained from IbisWorld) that I interact with the car's size (length x width x height).

The differentiation IVs also help to identify the price parameter, as they shift markups. For example, a car facing strong competition along certain product dimension should earn a lower markup. On the other hand, a car that has no close competitors in the attribute space will be able to earn a high markup for firms as diversion to other products will be limited.

Car demand: range. I build two cost shifters to instrument for range: First, I use the Bloomberg NEF battery cost estimate and interact it with the size (length x width x height) of the car. Second, I exploit manufacturer-supplier data to identify the battery supplier of each EV and interact the exchange rate between the Euro and that supplier's home country with the car's size. Both these instruments use important facotrs shifting the marginal cost of providing range. The impact of these cost shocks scales with the size of the car, given that larger cars tend to deploy larger batteries.

I also build a differentiation instrument built on a range index akin to the price index described above. In particular, I count the number of cars whose predicted range is below 100km and build the quadratic version of this instrument for own- and rival-firm products. The idea behind this instrument is to account for competition between pure electric and plug-in hybrid cars. The other differentiation instruments also help identify the range parameter: an EV facing tight competition will be constrained to offer a higher range, hence offering higher "quality" in this dimension. The range parameter is also identified through the quadratic instruments that count the squared characteristics of close rivals: For example, competing with many heavy cars will make it easier for firms to offer a lower range as heavier cars tend to suffer from low range, given the energy needed to move this weight. Finally, the exogenous characteristics of the car will also help to identify the range parameter as they are good predictors of range. Note that the assumption on car maker's choices ensures the validity of these instruments: Car attributes other than price and range are set beforehand, ensuring they are uncorrelated with the error term.

Car demand: charging stations. I account for the endogeneity of the charging station network by including subsidies as instruments. These subsidies vary across years as well as across states and exogenously shift the number of charging stations but do not directly affect the utility of consumers.

Car supply. On the supply side, firms choose range after they have fixed all other product attributes. Range choices can thus be correlated with unobserved marginal cost shocks. I account for this endogeneity issue by constructing differentiation IVs built on the exogenous characteristics entering the marginal cost function. I also include the observed exogenous characteristics entering the baseline marginal cost, as these characteristics were chosen before range. As on the demand side, I use a subset of the instruments that I create.

Charging station entry. Just like on the car demand side, there is a feedback loop between the number of stations in a given period and the cumulative EV base, which includes newly bought cars in that period. I account for this issue by instrumenting the cumulative EV base with the gas station density in the given state in the given year. A larger density of gas stations leads to lower gasoline prices (see Haucap, Heimeshoff, and Siekmann, 2017). Lower gasoline prices in turn make the overall costs of combustion cars cheaper relative to electric cars, which leads to a lower EV base. In particular, I draw a radius of 5 kilometers around each gas station and count the number of competitors. I then compute the median number of competitors in each state in each year and take the logged value. I also use the yearly average fuel prices in each state in each year as well as the length of the road network in a given state. Gasoline prices directly affect the usage cost of combustion cars and the size of the road network correlates with the level of car ownership.

4.2 Identification

Using the set of instruments described above allows me to pin down the estimated parameters. I recover the mean utility parameters β and the cost parameters ϕ through a linear projection. Variation in market shares and observed characteristics then identify β. Market share variation exists across states (the m part of the market index) and time (the t part of the market index). In contrast, product characteristics mainly vary across time (except for the endogenous charging station variable). The demand-side parameters, coupled with an assumption on firm behavior, allow me to back out implied marginal costs. Changes in the implied marginal cost and observed cost-shifters then identify the vector of marginal cost parameters ϕ. In addition to using the instruments described above, variation in the observed characteristics helps identify σ. Similarly, variation in market shares, prices, and consumer income identify the price coefficient α. Prices vary across time, whereas consumer income varies both across time and across states. The parameters (γ_0, γ_1) governing the marginal cost of range are identified from variation in observed range levels and the implied marginal cost of providing it, which, in turn, depends on variation in prices and market shares. For a more elaborate discussion on the identification of demand and supply models with differentiated products, refer to Berry and Haile (2014). The key identifying assumption on the charging station side is that the gas station density only affects charging station entry through the cumulative EV base (see Springel, 2021). Identification would break down if gas station density grew with EV adoption in a given state. This is not the case, however.

I estimate the car demand model, the car supply model, and the charging station entry model separately. Appendix C describes the estimation procedure in more detail.

5 Results

The estimated coefficients of key parameters are in Table 2. The first three columns show demand and supply estimates and the last three columns show estimates from the charging station entry equation. Table 10 in Appendix A reports first-stage regressions. Note that the fixed effects I use in the charging entry equation soak up the effects of the gasoline station density instrument. However, Table 12 in Appendix A shows that removing the instrument does not change the estimates. Table 11 in Appendix A reports the full demand and marginal cost estimates. Table 15 in Appendix D reports the results when assuming firms and charging stations move simultaneously. Appendix H presents results from an alternative specification with an interaction between range and charging stations. Overall, the signs and magnitudes of the estimated coefficients are in line with standard economic intuition.

Consumers like greater range, all else equal. The range-specific trend is negative, meaning consumer preferences for range become less intense throughout the sample period. One explanation is that range anxiety has decreased over time due to consumers learning more about electric vehicles. Consumers learn from their own experience, their peers, or simply from a greater availability of information on electric cars. Research and consumer surveys suggest that the driving range of current battery-electric cars is sufficient for most trips. Li, Linn, and Muehlegger (2014), for instance, report that households drive approximately 50 miles per day on average. Another explanation may be that faster battery charging has made consumers less worried about range. A further explanation for the negative trend is that it captures decreasing marginal utility of range as the range increases. Range has indeed increased, as evidenced in Figure 2. The random coefficient on range suggests that considerable heterogeneity exists in the valuation of range, even though this parameter is estimated imprecisely. The positive and statistically significant sign on the *Charging Station* variable implies that consumers prefer more charging stations, in line with previous studies on demand for electric vehicles (Li, 2023; Springel, 2021). The mean range elasticity is equal to 3.823.

The average willingness to pay for range is €75, ranging from €102 in 2012 to €49 in 2018. However, these averages hide considerable heterogeneity. In 2018, the 90th percentile is

Table 2: Key estimates

Demand/supply for cars			Station entry		
	Coefficient	SE		Coefficient	SE
Demand: Means					
Range	2.274	(0.350)	log(EV base)	0.707	(0.191)
Range x Trend	-0.201	(0.034)	National Subsidies	0.116	(0.021)
log(Charging Stations)	0.373	(0.079)	Local Subsidies	0.022	(0.030)
Fuel Cost	-0.564	(0.039)			
BEV	-10.037	(1.928)			
PHEV	-6.982	(1.824)			
Demand: Obs. Heterogeneity					
Price / Income	-7.112	(0.648)			
Demand: St. Dev.					
BHEV	2.455	(0.891)			
Range	0.326	(0.346)			
Fuel Cost	0.267	(0.017)			
Supply: Range provision					
Intercept	1.124	(0.041)			
Trend	-0.095	(0.008)			
Statistics					
Mean own-price elasticity	-4.043				
Mean own-range elasticity (BEVs)	3.823				
Mean markup (BEVs)	7.130				

Note: Prices, subsidies deflated and in EUR 1,000. Vehicle class-, Body-, Firm-, Year- and State Fixed Effects included on car demand- and supply side. Linear time trend and state demographics included on station entry side. See Table 11 for the full demand and supply estimates.

willing to pay €93 for range; and the most range-loving consumer is willing to pay €581.

All else equal, consumers strongly dislike both battery and plug-in hybrid electric vehicles, even though there is considerable heterogeneity in the population. A small share of consumers prefers electric cars over those with a combustion engine. The results suggest that the disutility from purchasing EVs decreased over the sample period since the driving range and the number of charging stations increased. This finding also underscores the importance of range and charging stations for the mass adoption of EVs. Overall, consumers enjoy a lower utility from EVs compared to combustion cars. However, this utility penalty decreases with a higher range and a larger charging station network.

The negative and significant coefficient on price over income translates into a mean price elasticity of -4.043, which falls within the range of figures found in the extensive literature on demand estimation for new car markets. Table 21 in Appendix J shows how my estimated price elasticity compares to other papers. Unlike the sensitivity of range, price sensitivity barely changes over the sample period. Due to slightly larger and more dispersed household income, mean price sensitivity dropped slightly from 2012 to 2018, with the variance increasing slightly. The relative stability of price sensitivity, together with the finding of a lower valuation of range over time, suggests that towards the end of the sample period, consumers valued (a lower) price more relative to range than at the beginning.

Table 2 also suggests that important indirect network effects exist on the EV demand and the charging station entry side. To give an idea of the magnitude of the coefficients, I calculated the predicted increase in the number of charging stations in each state if there had been an additional 1,000 EVs on the road in 2018. Such an increase in the EV base would have led to between 28-141 new charging stations, depending on the state, with the median increase being 83 stations. Overall, these additional 1,000 EVs would have led to aa further 1,272 charging stations. Note that there were 17,509 chargers and 197,176 EVs circulating in 2018. In turn, these additional charging stations would increase the willingness to pay for EVs by between € 24-501, with the median increase being € 140.[25]

Consumers dislike higher fuel costs, as evidenced by the negative parameter in the mean utility. A dis-utility from higher driving costs makes sense, as these increase the overall cost of using a car. However, consumers exhibit considerable heterogeneity in their valuation of fuel costs. Heterogeneity in the valuation of fuel costs is also unsurprising, as factors such as income, driving behavior, and preferences for less fuel-efficient cars play a role in shaping an individual's fuel cost valuation.

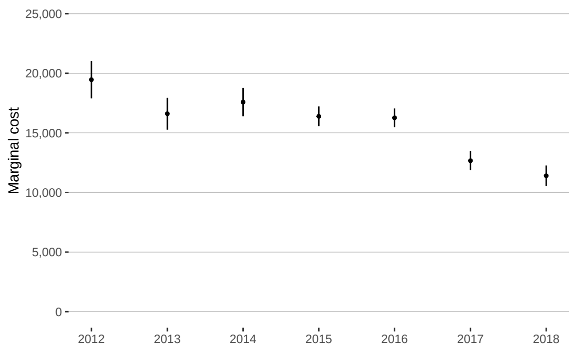

Figure 3: Estimated yearly mean marginal cost of providing range

Vertical lines are 95% CIs

On the marginal cost side, I find that range is costly to provide. Range provision became cheaper over the sample period, evidenced by the trend's negative and statistically significant coefficient. This trend translates into a mean decrease in the marginal cost of providing range of approximately 41% from 2012 to 2018 (see Figure 3). This number is comparable to estimates of lithium-ion cell price decreases in (see Hsieh et al., 2019, for instance). In 2018, the average marginal cost of providing an extra km of range was € 114, ranging from € 79 to € 233.

The estimates of the range-specific marginal cost shock η are intuitive: Tesla models have the lowest range-specific marginal cost shocks. Overall, there is a negative correlation between the total range of a car and its range-specific marginal cost shock, with the correlation being -.42. The mean value for η is -0.02 and its variance is .040.

Figure 7 in Appendix B plots marginal cost curves at different range levels for 2012 and 2018. The lines are computed using the mean estimated baseline marginal cost across BEVs

[25]Note that the maximum increase in the willingness to pay occurs in a state that has a stock of around 1,300 EVs and 180 charging stations in 2018. The minimum increase occurs in a state that has a stock of around 39,000 EVs and 3,800 charging stations in 2018.

and the mean estimated marginal cost of providing range for 2012 and 2018, respectively. The curve is much flatter in 2018 than in 2012, when range levels higher than 250 km resulted in a marginal cost above € 50,000. The figure suggests that it was not feasible to provide many of the range levels observed in 2018 at a competitive price.

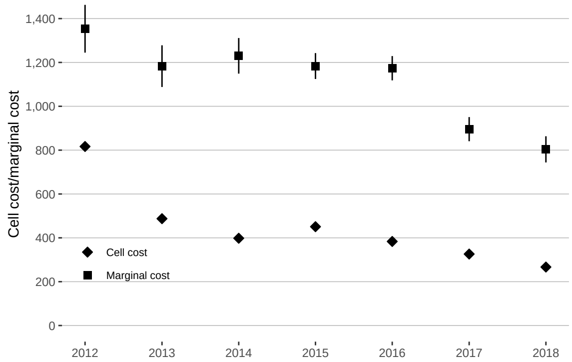

Figure 4: Per-kWh cost at observed range levels against battery pack cost

Battery pack cost estimates are taken from Steen et al. (2017). Values for 2018 are estimates. Per-kWh cost are calculated by dividing the marginal cost of providing range by the battery efficiency.

To dig deeper into the validity of the marginal cost estimates, I translate the marginal cost of providing range into a battery cost per kWh. Dividing the estimated mean marginal cost of providing range by the battery efficiency, I obtain a cost per kWh. I then compare this per-kWh translation of the marginal cost of providing range to estimated costs of a battery pack, taken from an engineering report (Steen et al., 2017). This report provides an estimate for the battery pack cost in $ per kWh for the sample period considered, which I convert into euros and deflate. The results are shown in Figure 4. We can see that the estimated per-kWh cost, evaluated at observed range levels, is above the battery pack cost coming from engineering estimates. This finding makes sense, given that the battery pack's size is the main but not the only determinant of providing range. Additionally, the graph shows the per-kWh cost evaluated at observed range levels and imputed marginal cost levels. Given the log-linear marginal cost specification, this per-kWh cost would be different at different marginal cost and range levels. However, apart from 2013-2014, the per-kWh cost backed out of the model follows a similar trend to the battery pack estimate, providing evidence that my marginal cost estimates are reasonable.

The baseline marginal cost estimates have the expected signs and magnitudes. Larger, heavier, more powerful, and more fuel-efficient cars are more costly to produce. Battery electric vehicles are cheaper to produce, all else equal, which is reasonable given that apart from the costly range provision, there are many parts (gearbox, exhaust pipe, starter, injection system, etc.) that are not necessary for the production of a BEV. The supply-side results suggest that range provision accounts for approximately 25% of the marginal cost of producing a BEV, on average. This finding is in line with recent engineering cost estimates (Lutsey and Nicholas, 2019), further suggesting that my marginal cost estimates are reasonable in magnitude.

The role of network effects

Table 3: Mean own-and cross-price elasticities of selected BEVs in 2018

	i3	Soul	i.MiEV	Leaf	Golf	up.	markup
With indirect network effects							
i3	-3.9437	-0.0616	-0.0671	-0.0598	-0.0611	-0.0677	7,622
Soul	-0.0332	-3.5770	-0.0245	-0.0273	-0.0290	-0.0255	6,537
i.MiEV	-0.0004	-0.0004	-2.9688	-0.0004	-0.0004	-0.0004	5,956
Leaf	-0.0305	-0.0284	-0.0306	-3.6190	-0.0284	-0.0310	6,862
Golf	-0.0775	-0.0741	-0.0772	-0.0727	-3.6287	-0.0777	7,431
up.	-0.0133	-0.0127	-0.0125	-0.0127	-0.0127	-2.8991	6,204
Without indirect network effects							
i3	-3.8480	0.0351	0.0299	0.0365	0.0348	0.0292	8,391
Soul	0.0143	-3.5306	0.0232	0.0204	0.0184	0.0222	7,213
i.MiEV	0.0001	0.0001	-2.9683	0.0001	0.0001	0.0001	6,433
Leaf	0.0197	0.0221	0.0201	-3.5688	0.0216	0.0196	7,318
Golf	0.0352	0.0391	0.0364	0.0401	-3.5164	0.0357	8,046
up.	0.0036	0.0042	0.0045	0.0042	0.0041	-2.8821	6,927

Note: Upper half of table shows elasticities taking indirect network effects into account, lower half of table shows elasticities when ignoring indirect network effects.

Table 2 suggests the presence of strong indirect network effects on both the EV demand- and the charging station entry side. We saw in Section 3.4 that indirect network effects alter the market share derivatives with respect to price and range and hence the price and range elasticities. Through their influence on pricing decisions, indirect network effects also affect markups. Shutting down indirect network effects in firm decisions would lead to markups that would be 8% higher on average. Table 3 shows the effect of indirect network effects on own-and cross-price elasticities as well as on markups of selected BEVs in 2018. We see that the own-price elasticities are larger when firms take account of indirect network effects. Moreover, cross-price elasticities become negative, meaning that BEVs act as complements: Increasing the price of a BEV will lead to lower sales of rival BEVs. We can also see that markups are substantially lower. For instance, the markup of the Nissan Leaf is estimated to be around €450 lower when taking into account indirect network effects. Note that indirect network effects also accrue to PHEVs, whose markups would be 5.5% higher without indirect network effects.

We can see similar patterns in Table 4 which shows own-and cross-range elasticities. When firms take into account indirect network effects, own-range elasticities increase and the sign of cross-range elasticities flips from negative to positive, again meaning that BEVs act as complements.

Table 4: Mean own-and cross-range elasticities of selected BEVs in 2018

	i3	Soul	i.MiEV	Leaf	Golf	up.
With indirect network effects						
i3	2.5400	0.0347	0.0416	0.0326	0.0344	0.0423
Soul	0.0263	3.2762	0.0250	0.0240	0.0250	0.0256
i.MiEV	0.0002	0.0002	1.8048	0.0002	0.0002	0.0002
Leaf	0.0281	0.0265	0.0313	3.8281	0.0266	0.0319
Golf	0.0571	0.0555	0.0624	0.0534	3.0182	0.0632
up.	0.0065	0.0063	0.0065	0.0062	0.0063	1.5976
Without indirect network effects						
i3	2.4783	-0.0277	-0.0209	-0.0295	-0.0275	-0.0202
Soul	-0.0132	3.2375	-0.0147	-0.0156	-0.0144	-0.0141
i.MiEV	-0.0001	-0.0001	1.8045	-0.0001	-0.0001	-0.0001
Leaf	-0.0228	-0.0248	-0.0201	3.7770	-0.0242	-0.0195
Golf	-0.0341	-0.0361	-0.0296	-0.0380	2.9272	-0.0287
up.	-0.0026	-0.0029	-0.0027	-0.0029	-0.0028	1.5884

Note: Upper half of table shows elasticities taking indirect network effects into account, lower half of table shows elasticities when ignoring indirect network effects.

6 Counterfactuals

In this section, I use the estimated model to quantify the effect of subsidies on battery electric vehicles by performing several counterfactual exercises. In a first step, I analyze how firms adjust price and range in response to subsidies and how indirect network effects impact these adjustments. In a second step, I assess the subsidy scheme imposed in Germany. Finally, I evaluate different subsidy schemes and compare them in terms of market outcomes. This step allows me to describe how subsidy design affects policy objectives and the underlying substitution patterns. It also allows a discussion on the compatibility of different policy objectives. In Appendix G, I also look at the impact of indirect network effects on price and range choices as well as market outcomes. I perform all counterfactuals for 2018. Appendix F gives details on the counterfactual procedure.

6.1 The impact of subsidies on pricing, range choices, and charging station entry

In this subsection, I evaluate the effect of the German support scheme. The scheme consisted of a €2,000 purchase subsidy for BEVs introduced in 2016 and an €8,000 subsidy for the installation and connection of a public charging station introduced in 2017. The explicit goal was to increase EV sales to have 1 million electric cars on the streets by 2020 and 6 million by 2030. In this section, I quantify the impact of introducing this support scheme by re-computing the market equilibrium in 2018 without the scheme. To look at the relative importance of purchase- and charging station subsidies, I also consider scenarios where I either remove the purchase subsidy only or the charging station subsidy only.[26]

[26] In all scenarios, I leave the subsidies for PHEVs unchanged. Likewise, I leave any state-level subsidies in place.

Table 5: Analysis of price and range adjustments

		No BEV subsidy			**No station subsidy**	**Neither subsidy**
	Observed	**Price adjusts**	**Price + Range adjust**	**Full feedback loop**		
Price	34,782	+2,263 (+2,203, +2,321)	+11,199 (+3,645, +17,945)	+11,243 (+3,610, +18,140)	-1,302 (-1,846, +7,116)	+11,283 (+3,689, +18,269)
Range	259	0	+34 (+15, +52)	+34 (+15, +53)	-7 (-14, +25)	+34 (+16, +53)
MC	21,774	0	+5,466 (+831, +10,094)	+5,495 (+855, +10,096)	-873 (-1,333, +4,319)	+5,502 (+903, +10,253)
Markup	7,361	+314 (+264, +363)	+2,357 (+551, +3,414)	+2,366 (+562, +3,429)	-221 (-251, +1,574)	+2,392 (+582, +3,468)
Sales	34,761	-7,604 (-8,051, -7,043)	-10,189 (-11,760, -6,939)	-10,569 (-12,928, -6,100)	-6,399 (-9,019, -2,886)	-14,904 (-16,205, -11,356)
Stations	17,509	0	0	-712 (-3,504, +3,994)	-7,942 (-7,949, -6,856)	-7,947 (-7,949, -6,982)
Government spending	130.604	-67 (-67, -67)	-67 (-67, -67)	-73 (-95, -35)	-76 (-83, -71)	-131
Consumer Surplus	49,250	-66 (-3,073, +4,061)	-71 (-3,054, +4,065)	-81 (-3,076, +4,037)	-155 (-3,123, +3,938)	-213 (-3,161, +3,886)
CO2 emissions	5,192,205	+3,426 (+2,830, +4,005)	+4,489 (+2,483, +5,173)	+4,667 (+2,290, +5,868)	+3,180 (+968, +5,645)	+6,955 (+4,247, +9,053)

Note: Table gives differences to observed outcomes with 90% C.I. in parentheses. Prices, range levels, marginal costs, markups, and sales are mean values across BEVs.

I run additional scenarios to explore how firms strategically adjust price and range in response to subsidies and how these choices interact with each other and with station entry. To do so, I run a counterfactual in which firms only adjust prices, leaving range choices and charging station entry fixed. I also run a counterfactual where firms adjust both price and range, leaving charging station entry fixed.

Table 5 shows the counterfactual results. Columns 3-5 show the impacts of removing purchase subsidies while allowing for only price adjustment (column 3), price and range adjustment (column 4), and price, range, and station entry adjustments (column 5). Column 6 shows the impact of removing the charging station entry subsidy, and column 7 shows the outcome when all subsidies are removed.

When firms can only adjust prices, they slightly overshift the subsidy, with the median pass-through rate being around 118%. If firms can adjust prices and the EV range, the subsidy leads to a substantially larger price decrease but also a substantial range decrease.[27] The median price decrease is €5,181 and the median range decrease is 19km; the large mean decrease is driven by two models that reduce range substantially in response to the subsidy.[28] Range adjustments explain this median price reduction that is 2.5 times larger than the subsidy. Firms

[27]In Appendix K I show that the direction of firms' price and range reactions is unclear a priori. Among other things, the direction depends on the price and range semi-elasticities as well as the marginal cost of providing range. Gaudin (2022) shows that the direction of such strategic reactions are ambiguous even in simpler models assuming symmetry and single-product firms.

[28]Note that the price changes shown here are final consumer prices where the subsidy has been subtracted.

reduce the EV range, which reduces the marginal cost of cars. Why do firms reduce range in response to the subsidy? The subsidy makes EVs cheaper, which makes them more attractive to more price-sensitive consumers with a lower willingness to pay for range. This, in turn, gives firms incentives to reduce the price further by reducing range, which lowers the marginal cost of producing the car. Firms pass on this marginal cost decrease to consumers. Defining a pass-through rate when firms can adjust attributes is tricky. I define an implicit pass-through rate as $\frac{\Delta_p}{\Delta_{mc}*(1+vat)+\lambda}$, where Δ_p is the consumer price difference pre- to post-subsidy, Δ_{mc} the change in marginal cost (augmented by the value-added tax rate), and λ is the subsidy. The average implicit pass-through rate is around 119%, almost exactly what the pass-through rate is when firms only adjust prices. In total, the subsidy leads to cheaper, lower-range EVs on the market, and car makers collect a lower markup on them. Selling cheap, low-range BEVs increases substitution from the outside option and decreases cannibalization on higher-margin combustion cars, making this strategy profitable for firms when facing flat subsidies. Overall, the price and range changes that my counterfactuals predict are in line with the reduced-form evidence I presented in Table 1.

Figure 8 in Appendix B shows that the direction of price and range effects goes into the same direction for all subsidized BEVs. The only BEV whose price and range increase in response to the subsidy is Tesla's Model S which did not qualify for the subsidy. Figure 9 in Appendix B breaks down the price changes in response to removing the purchase subsidy (the Figure corresponds to column 4 in Table 5). The Figure underscores the fact that most price changes are around €5,000 and that marginal cost changes due to range adjustments explain most of the discrepancy between the price increase and the subsidy amount.

These cheaper, lower-range EVs generate more sales: an additional 2,400 sales compared to when firms can only adjust prices. It is noteworthy that taking into account indirect network effects increases the price and range adjustments, but not by much. Purchase subsidy drives the price and range adjustments. The most important effect of the EV/charging station feedback loops is on charging station exit, consumer surplus, and CO2 emissions: the subsidy increases EV sales, which induces entry of charging stations, which in turn increases EV sales further. Consumer surplus increases by around 14% when accounting for indirect network effects (even though there is uncertainty about the sign of the effect), and CO2 emissions decrease by a further 4%.

In terms of policy outcomes, rows 5-8 reveal that EV sales rose by 75% and station entry rose by around 83% due to the support scheme. Consumer surplus increased by around €213 million whereas the scheme cost €130 million. Removing both subsidies amplifies indirect network effects: Removing the purchase subsidy leads to lower charging station entry. Likewise, removing the charging station subsidy leads to lower BEV sales, even though the loss in sales is lower than when the purchase subsidy is removed. Removing the charging station subsidy would lower consumer surplus substantially more than removing the purchase subsidy. One reason for this result is that the charging station subsidy generates strong feedback loops without causing large adjustments in BEV price and range levels. As a result, consumers enjoy both high range and a large charging station network.

The counterfactuals reveal that charging station subsidies generate 10 times the charging station entry, 60% of the EV sales, and 90% higher consumer surplus at almost the same cost to taxpayers. Do charging station subsidies provide more bang for the buck? The exercise above does not hold subsidy spending constant. Spending on station subsidies was higher than spending on purchase subsidies. To really assess the effectiveness of the different subsidies, we should compare the schemes holding expenditure levels constant, which is what I do in the next step.

6.2 Designing EV subsidy schemes

In this section, I investigate the effectiveness of different subsidy schemes in more detail. To do so, I allow for different levels of purchase and charging station subsidies at constant budget levels. I consider different combinations of $\boldsymbol{\lambda} \equiv (\lambda_1, \lambda_2, \lambda_3)$, where λ_1 is the flat part of the purchase subsidy, λ_2 is the range-based part of the purchase subsidy, and λ_3 is the charging station subsidy. The purchase subsidy for a BEV with range r_j is then $\lambda_j = \lambda_1 + \lambda_2 r_j$. I allow purchase subsidies to depend on the range because policymakers in some countries use attribute-based subsidies (Rokadiya and Yang, 2019). Doing so also gives the policymaker the choice between subsidizing two attributes that enhance BEV quality, creating an interesting choice between directly incentivizing range provision and steering consumers towards higher-range cars and incentivizing charging station entry, which will benefit all BEVs equally.

I use a grid search approach to find the impact of different schemes $(\lambda_1, \lambda_2, \lambda_3)$ while holding subsidy spending constant at its 2018 level. Appendix F.2 presents further details.

I focus on three outcomes in this section: First, I look at CO2 emissions from new car sales, as the ultimate goal of subsidizing BEVs is to decarbonize the transport sector. Second, I focus on EV sales. Many governments have introduced explicit sales targets for electric vehicles. A diffusion-maximizing approach ensures the achievement of these sales targets. In addition, a strategy focusing on maximizing diffusion can also be a static approximation to a dynamic optimization problem: A policymaker quickly wants to move along a learning curve. A diffusion-maximizing strategy can do well in approximating the desire to move along the learning curve swiftly in the early phase of adoption. Third, I look at consumer surplus, as well as total surplus. When calculating total surplus I take account of the social cost of carbon, which I assume to be €75/t.

In Table 6, I present the schemes that maximize different policy objectives, as well as the observed scheme ($\boldsymbol{\lambda} = (2, 0, 8)$).[29] Different schemes maximize different policy objectives. By increasing the (flat) purchase subsidy and decreasing the charging station subsidy, the policymaker can maximize BEV sales. A similar scheme with slightly more weight on station

[29] Table 16 in Appendix D reports the results when assuming firms and charging stations move simultaneously.

Table 6: Comparison of subsidy schemes

Scheme	Price	Range	Sales	Stations	CO2	CS	TS
(0, 0, 0)	44,059	293	19,854	9,562	5,199,163	43,325	65,476
(2, 0, 8)	-11,278	-34	+14,907	+7,947	-6,958	+153	+241
(1.25, 0.2, 8.55)	-6,414	-15	+12,215	+8,971	-5,841	+154	+239
(3, 0, 5.55)	-14,948	-50	+18,005	+3,699	-7,951	+135	+216
(3.25, 0, 4.5)	-15,555	-52	+18,230	+2,284	-7,920	+127	+202

Note: Table shows differences with respect to scenario without any subsidies. Prices, range levels, and sales are mean values across BEVs.

subsidies minimizes CO2 emissions from new car sales. By shifting weight on subsidizing charging stations, the policymaker can maximize consumer surplus. It turns out that the actual subsidy scheme maximized total surplus, which is mainly driven by carmaker profits being maximized with the observed scheme. Schemes that employ purchase subsidies lead to strong price and range reactions by firms. Consumer surplus maximization requires a scheme causing small price and range reactions by firms and a large amount of charging station entry, which happens when charging stations are the main recipient of subsidies. Under the scheme $\boldsymbol{\lambda} = (1.25, 0, 8.55)$, over 70% of the budget is spent on charging station subsidies. In that case, fewer consumers buy a BEV, but the BEVs sold have a high range and profit from a large charging station network.[30] These results are in line with findings by Jia Barwick et al. (2023), who study a Chinese subsidy design and also find that attribute-based subsidies lead to a higher range. The results also concur with Springel (2021), who finds that using both purchase and station subsidies maximizes EV adoption in the case of Norway.

Table 7 reports substitution patterns across the different schemes. Columns 2 and 3 report where substitution comes from and columns 4 and 5 report where substitution goes to. Note that since PHEVs also benefit from a larger charging station network, their sales numbers also increase. We can see that between 72% and 75% of the substitution towards EVs comes from the outside option, meaning that the new car market expands overall. Substitution from the outside option can come from consumers who otherwise would have bought a used car (enhancing the subsidy scheme's environmental benefits by removing dirty vehicles from the market) or consumers who would not have bought a car at all (unintentionally expanding car usage, local pollution, and road congestion). This table also explains why the scheme $\boldsymbol{\lambda} = (3, 0, 5.55)$ minimizes CO2 emissions from new car sales. Doing so requires two conditions to be met: First, a large part of the substitution towards EVs should go towards BEVs. Second, minimizing CO2 emissions entails a trade-off between generating as much substitution from combustion cars as possible on the one hand and generating substitution from very polluting cars on the other

[30] The environmental benefits from mainly subsidizing charging stations may be understated to the extent that a higher range and a larger charging station network may induce consumers who own both an EV and a combustion car to drive the EV more and the combustion car less (Sinyashin, 2021). Also, shifting subsidy spending towards charging stations leads to a larger ratio of public chargers to EVs, alleviating congestion concerns from having too many EVs per charger.

Table 7: Substitution patterns across subsidy schemes

Scheme	Substitution from		Substitution to	
Scheme	ICE	Outside option	BEV	PHEV
(2, 0, 8)	5,339	14,174	14,907	4,605
(1.25, 0.2, 8.55)	4,877	12,654	12,215	5,316
(3, 0, 5.55)	5,085	14,852	18,005	1,931
(3.25, 0, 4.5)	4,763	14,399	18,230	932

Note: Table shows how many consumers substituted away from combustion cars (ICE) and outside options and how many substituted towards BEVs and PHEVs, compared to the scenario without any subsidies.

hand. While schemes causing less price and range adjustments generate both the largest amount of substitution from combustion cars and also generate substitution from more polluting cars, these schemes generate substantial substitution towards PHEVs that are not zero-emission, which is why they do not minimize CO2 emissions from new car sales. The observed scheme $\boldsymbol{\lambda} = (2, 0, 8)$ generates more substitution from combustion cars than the emission-minimizing one. However, the observed scheme generates more subsitution towards PHEVs.

This section shows that policymakers face a trade-off between maximizing BEV sales, minimizing CO2 emissions from new car sales, and maximizing consumer and total surplus. Firms' strategic price and range reactions to subsidies drive this trade-off, underscoring the need for policymakers to carefully study firm responses to subsidies when trying to achieve specific policy goals.

7 Conclusion

In this paper, I study subsidy design in the presence of adjustable product attributes and indirect network effects. In particular, I analyze how indirect network effects affect price and range decisions of EV producers and how subsidies affect EV prices and range, charging station entry, and policy outcomes.

I develop a structural model of endogenous product attribute choice in the presence of indirect network effects and estimate it using a novel data set on state-level new car sales in Germany. On the demand side, consumers choose between differentiated cars of different engine types. The demand side allows for flexible substitution patterns that are key to evaluating how purchase subsidies affect car choices. On the car supply side, firms make endogenous price and EV range choices, allowing me to study their interaction with indirect network effects and subsidies. The charging station entry side links the number of charging stations to the cumulative EV base and the level of charging station subsidies. The model allows me to study how indirect network effects interact with endogenous price and range decisions and how these decisions affect policy objectives of EV subsidy programs.

I find important indirect network effects both on the EV demand- and on the charging entry side. As a result, own-price elasticities are larger in absolute value when taking indirect network effects into account. Indirect network effects lower EV markups by around 6% on average. Indirect network effects lead to positive cross-price and negative cross-range elasticities, which has important implications for the price and range choices of EV producers. I also find that consumers have strong preferences for range, which is costly to provide. On the supply side, I find that the marginal cost of providing range decreased by around 41% from 2012 to 2018.

I analyze a German program for purchase and charging station subsidies. I find that this program doubled EV sales but caused strong price and range adjustments. The program led to cheaper, lower-range EVs on which firms collected a lower markup. I find that removing the charging station subsidy would decrease EV sales by 18% and charging stations by 46%. Alternatively, removing purchase subsidies would decrease EV sales by 30% and charging stations by 4%.

To comprehensively analyze subsidy design, I allow for range-based purchase subsidies and allow the policymaker to freely choose the amount of flat and range-based purchase subsidies and charging station subsidies while holding the budget constant at the observed subsidy cost in 2018. I find that the policymaker faces a trade-off between maximizing EV sales, maximizing consumer surplus, maximizing total surplus, and minimizing annual CO2 emissions from new cars. Whereas a large flat purchase subsidy maximizes EV sales at a lower range and prices, consumers prefer the vast majority of the budget being spent on charging subsidies. A high purchase subsidy coupled with a low charging subsidy minimizes CO2 emissions from new car sales. The observed subsidy scheme maximizes total surplus.

These results have important implications for policymakers. It is crucial to understand strategic firm reactions generated by different subsidy schemes, as they can lead to stark price and range adjustments. These adjustments will drive substitution patterns between EVs and combustion cars, which in turn will shape the policy outcomes of subsidies. In particular, EV sales targets or outright maximization of EV sales can trigger unintended consequences in the form of price and range adjustments.

My paper leaves scope for future work. First, I do not directly explore dynamic incentives that may exist due to learning effects. Second, there exists a dynamic angle to the chicken-and-egg problem: Charging station providers and firms may wait on one another to enter the market, stalling the development of the EV industry in the absence of coordination or some other kind of intervention.

References

Armitage, Sarah, and Frank Pinter. 2022. "Regulatory Mandates and Electric Vehicle Product Variety." *Working Paper*.

Bäumer, Marcus, Heinz Hautzinger, Manfred Pfeiffer, Wilfried Stock, Barbara Lenz, Tobias Kuhnimhof, and Katja Köhler. 2017. "Fahrleistungserhebung 2014-Inlandsfahrleistung und Unfallrisiko."

Beresteanu, Arie, and Shanjun Li. 2011. "Gasoline prices, government support, and the demand for hybrid vehicles in the United States." *International Economic Review* 52 (1): 161–182.

Berry, Steven, and Philip Haile. 2014. "Identification in differentiated products markets using market level data." *Econometrica* 82 (5): 1749–1797.

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

Bresnahan, Timothy F, and Peter C Reiss. 1991. "Entry and competition in concentrated markets." *Journal of Political Economy* 99 (5): 977–1009.

Brunner, Daniel, Florian Heiss, André Romahn, and Constantin Weiser. 2017. *Reliable estimation of random coefficient logit demand models*. DICE Discussion Papers 267.

Bulow, Jeremy I, and Paul Pfleiderer. 1983. "A note on the effect of cost changes on prices." *Journal of Political Economy* 91 (1): 182–185.

Carley, Sanya, Rachel M Krause, Bradley W Lane, and John D Graham. 2013. "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites." *Transportation Research Part D: Transport and Environment* 18 39–45.

Chamberlain, Gary. 1987. "Asymptotic efficiency in estimation with conditional moment restrictions." *Journal of Econometrics* 34 (3): 305–334.

Conlon, Christopher, and Jeff Gortmaker. 2020. "Best Practices for Differentiated Products Demand Estimation with PyBLP." *The RAND Journal of Economics* 51 (4): 1108–1161.

Crawford, Gregory, Oleksandr Shcherbakov, and Matthew Shum. 2019. "Quality overprovision in cable television markets." *American Economic Review* 109 (3): 956–95.

Davis, Lucas W. 2019. "How much are electric vehicles driven?" *Applied economics letters* 26 (18): 1497–1502.

Davis, Lucas W. 2022. "Electric vehicles in multi-vehicle households." *Applied Economics Letters* 1–4.

Dubé, Jean-Pierre, Jeremy T Fox, and Che-Lin Su. 2012. "Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation." *Econometrica* 80 (5): 2231–2267.

Dubé, Jean-Pierre, Ali Hortaçsu, and Joonhwi Joo. 2021. "Random-coefficients logit demand estimation with zero-valued market shares." *Marketing Science*.

Durrmeyer, Isis, and Mario Samano. 2018. "To rebate or not to rebate: Fuel economy standards versus feebates." *The Economic Journal* 128 (616): 3076–3116.

D'Haultfœuille, Xavier, Isis Durrmeyer, and Philippe Février. 2019. "Automobile prices in market equilibrium with unobserved price discrimination." *The Review of Economic Studies* 86 (5): 1973–1998.

Fan, Ying. 2013. "Ownership consolidation and product characteristics: A study of the US daily newspaper market." *American Economic Review* 103 (5): 1598–1628.

Fournel, Jean-François. 2023. "Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions." *Working Paper*.

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

Gandhi, Amit, and Jean-François Houde. 2019. "Measuring Substitution Patterns in Differentiated Products Industries." NBER Working Papers 26375.

Gandhi, Amit, Zhentong Lu, and Xiaoxia Shi. 2013. "Estimating demand for differentiated products with error in market shares."

Gandhi, Amit, Zhentong Lu, and Xiaoxia Shi. 2022. "Estimating Demand for Differentiated Products with Zeroes in Market Share Data." *Quantitative Economics*.

Gaudin, Germain. 2022. "Quality and Imperfect Competition." *Working Paper*.
Grieco, Paul LE, Charles Murry, and Ali Yurukoglu. 2023. "The evolution of market power in the us automobile industry." *The Quarterly Journal of Economics* qjad047.
Grigolon, Laura, Eunseong Park, and Kevin Remmy. 2024. "Fueling Electrification: The Impact of Gas Prices on Hybrid Car Usage." *ZEW-Centre for European Economic Research Discussion Paper* (24-017): .
Grigolon, Laura, Mathias Reynaert, and Frank Verboven. 2018. "Consumer valuation of fuel costs and tax policy: Evidence from the European car market." *American Economic Journal: Economic Policy* 10 (3): 193–225.
Haucap, Justus, Ulrich Heimeshoff, and Manuel Siekmann. 2017. "Fuel prices and station heterogeneity on retail gasoline markets." *The Energy Journal* 38 (6): .
Hess, Stephane, Kenneth E Train, and John W Polak. 2006. "On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit model for vehicle choice." *Transportation Research Part B: Methodological* 40 (2): 147–163.
Hsieh, I-Yun Lisa, Menghsuan Sam Pan, Yet-Ming Chiang, and William H Green. 2019. "Learning only buys you so much: practical limits on battery price reduction." *Applied Energy* 239 218–224.
Jia Barwick, Panle, Hyuk-Soo Kwon, and Shanjun Li. 2023. "Attribute-Based Subsidies and Market Power: An Application to Electric Vehicles." *Working Paper*.
Johansen, Bjorn Gjerde, and Anders Munk-Nielsen. 2020. "Portfolio Complementarities and Electric Vehicle Adoption." *Working Paper*.
Kim, Donghun, and Ronald W Cotterill. 2008. "Cost pass-through in differentiated product markets: The case of US processed cheese." *The Journal of Industrial Economics* 56 (1): 32–48.
Klier, Thomas, and Joshua Linn. 2012. "New-vehicle characteristics and the cost of the Corporate Average Fuel Economy standard." *The RAND Journal of Economics* 43 (1): 186–213.
Knittel, Christopher R. 2011. "Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector." *American Economic Review* 101 (7): 3368–99.
Knittel, Christopher R, and Konstantinos Metaxoglou. 2014. "Estimation of random-coefficient demand models: two empiricists' perspective." *Review of Economics and Statistics* 96 (1): 34–59.
Leard, Benjamin, Joshua Linn, and Katalin Springel. 2019. "Pass-through and welfare effects of regulations that affect product attributes." *Working Paper*.
Li, Jing. 2023. "Compatibility and investment in the us electric vehicle market." *Working Paper*.
Li, Shanjun, Joshua Linn, and Erich Muehlegger. 2014. "Gasoline Taxes and Consumer Behavior." *American Economic Journal: Economic Policy* 6 (4): 302–342.
Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The market for electric vehicles: indirect network effects and policy design." *Journal of the Association of Environmental and Resource Economists* 4 (1): 89–133.
Lutsey, Nic, and Michael Nicholas. 2019. "Update on electric vehicle costs in the United States through 2030." *International Council on Clean Transportation (ICCT)*.
Maskin, Eric, and John Riley. 1984. "Monopoly with incomplete information." *The RAND Journal of Economics* 15 (2): 171–196.
Muehlegger, Erich, and David S. Rapson. 2022. "Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California." *Journal of Public Economics* 216.
Mussa, Michael, and Sherwin Rosen. 1978. "Monopoly and product quality." *Journal of Economic Theory* 18 (2): 301–317.

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

Pavan, Giulia. 2017. “Green Car Adoption and the Supply of Alternative Fuels.” TSE Working Papers 17-875, Toulouse School of Economics (TSE).

Preuß, Sabine, Robert Kunze, Jakob Zwirnmann, Jonas Meier, Patrick Plötz, and Martin Wietschel. 2021. “The share of renewable electricity in electric vehicle charging in Europe is higher than grid mix.”Technical report, Working Paper Sustainability and Innovation.

Rapson, David S, and Erich Muehlegger. 2023. “The economics of electric vehicles.” *Review of Environmental Economics and Policy* 17 (2): 274–294.

Reynaert, Mathias. 2021. “Abatement strategies and the cost of environmental regulation: Emission standards on the European car market.” *The Review of Economic Studies* 88 (1): 454–488.

Reynaert, Mathias, and James Sallee. 2021. “Who Benefits When Firms Game Corrective Policies?” *American Economic Journal: Economic Policy* 13 (1): 372–412.

Reynaert, Mathias, and Frank Verboven. 2014. “Improving the performance of random coefficients demand models: the role of optimal instruments.” *Journal of Econometrics* 179 (1): 83–98.

Rezvani, Zeinab, Johan Jansson, and Jan Bodin. 2015. “Advances in consumer electric vehicle adoption research: A review and research agenda.” *Transportation research part D: transport and environment* 34 122–136.

Rokadiya, S, and Z Yang. 2019. “Overview of global zero-emission vehicle mandate programs.” *International Council on Clean Transportation (ICCT)*.

Schoettle, Brandon, and Michael Sivak. 2018. “Resale Values of Electric and Conventional Vehicles: Recent Trends and Influence on the Decision to Purchase a New Vehicle.”

Sheshinski, Eytan. 1976. “Price, quality and quantity regulation in monopoly situations.” *Economica* 43 (170): 127–137.

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

Spence, Michael. 1975. “Monopoly, quality, and regulation.” *The Bell Journal of Economics* 417–429.

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

Steen, Marc, Natalia Lebedeva, Franco Di Persio, and L Boon-Brett. 2017. “EU competitiveness in advanced Li-ion batteries for E-mobility and stationary storage applications–opportunities and actions.” *Publ. Off. Eur. Union* 44.

Stern, Nicholas. 1987. “The effects of taxation, price control and government contracts in oligopoly and monopolistic competition.” *Journal of Public Economics* 32 (2): 133–158.

Thurk, Jeff. 2018. “Sincerest Form of Flattery? Product Innovation and Imitation in the European Automobile Industry.” *The Journal of Industrial Economics* 66 (4): 816–865.

Weyl, E Glen, and Michal Fabinger. 2013. “Pass-through as an economic tool: Principles of incidence under imperfect competition.” *Journal of Political Economy* 121 (3): 528–583.

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

Yang, Zifei, Peter Slowik, Nic Lutsey, and Stephanie Searle. 2016. “Principles for effective electric vehicle incentive design.” *Internatnional Council Clean Transportation*.

Online Appendix

A Additional Tables

Table 8: Summary statistics

Mean values of key characteristics

Variable	2012	2013	2014	2015	2016	2017	2018
BEV							
Price	30,575	31,383	35,491	32,569	37,105	37,200	34,671
Quality (Range in km)	168	173	202	196	213	246	259
Fuel Cost	4.03	4.35	4.39	4.19	4.24	4.28	4.21
Acceleration	2.80	2.98	3.19	2.96	3.31	3.26	2.94
Weight	1,581	1,662	1,797	1,797	1,867	1,902	1,841
Footprint	6.01	6.40	6.78	6.78	7.03	7.13	6.97
Doors	4.50	4.70	4.85	4.85	4.86	4.88	4.89
Number of Products	6	10	13	13	14	16	18
Sales	2,100	5,517	9,044	13,234	12,201	25,593	34,629
PHEV							
Price	43,409	48,607	44,389	56,007	57,479	54,651	57,126
Quality (Range in km)	54	53	52	44	40	45	45
Fuel Cost	5.31	5.66	5.78	5.77	5.57	5.58	5.89
Acceleration	4.58	5.16	5.02	5.81	5.82	5.81	5.95
Weight	1,988	2,160	2,143	2,408	2,476	2,425	2,449
Footprint	7.93	8.17	8.04	8.53	8.66	8.66	8.74
Doors	5	5	5	5	4.87	4.86	4.79
Number of Products	2	3	6	11	15	22	24
Sales	1,148	1,079	2,671	8,248	10,614	25,374	25,841
ICE							
Price	32,673	32,965	34,008	33,881	34,653	33,669	33,652
Quality (Range in km)	995	1,018	1,039	1,057	1,063	1,023	997
Fuel Cost	10.09	9.34	8.65	7.60	6.98	7.47	8.01
Acceleration	5.29	5.32	5.41	5.44	5.62	5.76	5.74
Weight	2,023	2,035	2,044	2,043	2,031	2,008	2,017
Footprint	8.00	8.04	8.07	8.08	8.10	8.09	8.12
Doors	4.43	4.48	4.52	4.55	4.52	4.58	4.63
Number of Products	233	233	227	222	214	213	215
Sales	2,739,581	2,569,876	2,651,415	2,767,185	2,855,922	2,864,409	2,819,762
Stations							
Number of Charging Stations	1,169	1,461	2,104	3,326	5,638	9,560	17,509

Note: This table shows average values of key characteristics, the number of products available, and total sales, broken up by engine type. The last row holds the cumulative number of charging stations.

Table 9: Charging station entry

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Charging stations										
Total	1,169	1,461	2,104	3,326	5,638	9,560	17,509	27,098	36,439	42,373
Level 2	1,165	1,457	2,080	3,193	5,194	8,562	15,717	24,122	31,822	35,277
Level 3	4	4	24	133	444	998	1,792	2,976	4,617	7,096
Pct Level 2	0.997	0.997	0.989	0.96	0.921	0.896	0.898	0.89	0.873	0.833

Note: This table shows cumulative numbers of charging stations. The second and third lines break this up between Level 2 and Level 3 chargers, the fourth row shows the share of Level 2 chargers among the number of chargers installed.

Table 10: First Stage Estimates

	Price		**Range**		**Range x Trend**		**Stations**	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Exogenous Charac.								
Fuel Cost	-0.795	(0.027)	0.010	(0.001)	0.045	(0.003)	0.007	(0.002)
Footprint	8.999	(0.096)	0.040	(0.002)	0.189	(0.010)	0.018	(0.005)
Acceleration	3.704	(0.046)	-0.017	(0.001)	-0.088	(0.005)	-0.005	(0.002)
Doors	0.246	(0.066)	-0.012	(0.001)	-0.066	(0.005)	-0.002	(0.003)
BEV	13.625	(1.709)	0.197	(0.097)	-3.245	(0.477)	4.298	(0.254)
PHEV	13.801	(1.870)	-0.694	(0.094)	-4.423	(0.479)	5.012	(0.310)
Own State	2.386	(0.366)	0.002	(0.011)	-0.015	(0.060)	0.240	(0.026)
PHEV								
Range x PHEV	-4.815	(1.334)	0.004	(0.000)	0.021	(0.002)	0.004	(0.001)
Range x PHEV x Trend	-1.094	(0.331)	2.112	(0.095)	15.758	(0.828)	-0.204	(0.422)
Cost shifters								
Station Subsidies	0.241	(0.077)	-0.259	(0.019)	-3.560	(0.149)	-0.004	(0.071)
Steel x Volume	2.237	(0.107)	-0.009	(0.005)	-0.104	(0.033)	0.085	(0.012)
GMY x-rate	4.171	(0.146)	-0.042	(0.003)	-0.183	(0.016)	-0.019	(0.008)
LI price x Volume	-0.001	(0.000)	0.012	(0.003)	0.024	(0.016)	-0.026	(0.011)
LI x-rate x Volume	0.327	(0.105)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Differentiation IVs								
BEV count-local-own	-1.388	(0.338)	0.155	(0.008)	0.725	(0.044)	0.041	(0.016)
Range index quadratic-own	-4.788	(0.576)	-0.055	(0.024)	0.114	(0.140)	0.050	(0.049)
Range index quadratic-rival	-2.372	(0.396)	-0.031	(0.047)	1.328	(0.278)	0.187	(0.101)
Footprint-local-own	17.023	(1.158)	0.231	(0.024)	2.494	(0.137)	0.244	(0.057)
Footprint-local-rival	-3.876	(0.316)	0.874	(0.042)	4.264	(0.229)	0.223	(0.124)
Price-local-own	-32.094	(1.019)	-0.025	(0.007)	-0.001	(0.032)	0.002	(0.017)
Price-quadratic-own	0.146	(0.006)	-0.647	(0.035)	-3.153	(0.189)	-0.183	(0.100)
Fuel efficiency-quadratic-own	-0.905	(0.667)	-0.001	(0.000)	-0.004	(0.001)	0.000	(0.000)
Fuel efficiency-quadratic-rival	0.138	(0.126)	-0.225	(0.019)	-1.228	(0.099)	-0.083	(0.037)
Weight-local-rival	-8.483	(0.310)	0.008	(0.001)	0.049	(0.006)	-0.004	(0.003)
Firm FE	X		X		X		X	
Class FE	X		X		X		X	
Body FE	X		X		X		X	
State FE	X		X		X		X	
Year FE	X		X		X		X	
SW F-Stat	180.683		89.668		41.42		41.582	
Observations	28,288		28,288		28,288		28,288	

Note:
makecell[l]This table presents first stage estimates for each of the endogenous charateristics. The Sanderson-Windmeijer multivariate F-test is reported for each endogenous vairable.

Table 11: Demand and marginal cost estimates

Utility			Marginal Cost		
	Coefficient	Rob. SE		Coefficient	Rob. SE
Mean Utility					
Intercept	-9.396	(0.377)	Intercept	1.124	(0.041)
Range	2.274	(0.35)	Trend	-0.095	(0.008)
Range x Trend	-0.201	(0.034)			
Stations	0.373	(0.079)	Intercept	1.595	(0.150)
Fuel Cost	-0.564	(0.039)	Weight	0.252	(0.044)
Footprint	0.708	(0.055)	Fuel Efficiency	-0.035	(0.006)
Acceleration	0.376	(0.026)	KW	0.005	(0.000)
Doors	-0.200	(0.027)	Footprint	0.079	(0.023)
BEV	-10.037	(1.928)	BEV	-0.946	(0.055)
PHEV	-6.982	(1.824)	PHEV	0.196	(0.026)
Own State	1.059	(0.076)			
2013	-0.706	(0.040)	2013	-0.006	(0.013)
2014	-0.889	(0.042)	2014	-0.023	(0.014)
2015	-1.326	(0.058)	2015	-0.058	(0.015)
2016	-1.212	(0.061)	2016	-0.061	(0.015)
2017	-1.186	(0.058)	2017	-0.066	(0.015)
2018	-1.262	(0.060)	2018	-0.088	(0.015)
Obs. Heterogeneity					
Price / Income	-7.112	(0.648)			
Standard Dev.					
BHEV	2.455	(0.891)			
Range	0.326	(0.346)			
Fuel Cost	0.267	(0.017)			

Note: Prices deflated and in EUR 1,000. Vehicle class-, Body-, Firm-, Year- and State Fixed Effects included.

Table 12: Station entry estimation: Robustness checks

	OLS	IV	IV	IV	IV	IV
Log(EV base)	0.593	0.490	0.586	0.686	0.706	0.707
	(0.079)	(0.178)	(0.222)	(1.508)	(0.191)	(0.191)
Subsidies national	0.122	0.141	0.123	0.111	0.116	0.116
	(0.025)	(0.022)	(0.033)	(0.061)	(0.021)	(0.021)
Subsidies local	0.004	0.026	0.005	-0.016	0.022	0.022
	(0.042)	(0.059)	(0.063)	(0.043)	(0.030)	(0.030)
R-squared	0.926	0.924	0.925	0.925	0.859	0.859
First stage						
F-stat		23.851	24.273	417.734	124.79	111.214
p-value		0	0	0	0	0
R-squared		0.840	0.834	0.990	0.917	0.917
Instruments						
Gas station density		X	X	X		X
Gas prices		X		X	X	X
Road network		X	X	X	X	X
Controls						
County FE	X	X	X	X		
Time trend				X	X	X
State controls					X	X

Note: This table shows different specifications for the station entry equation, along with the OLS estimate in the first column.

Table 13: Station entry: First Stage

	Dependent variable:	
	Log(EV Base)	
Subsidies national	−0.037	(0.021)
Subsidies local	0.018	(0.022)
Gas station density	−0.033	(0.588)
Road network length	2.725	(0.500)
Gasoline price	0.803	(0.196)
Observations	112	
R^2	0.917	
F Statistic	111.214	
Note:	NA	

Note:
This table reports the first stage for the specification used in the paper (last column of Table 12.

Table 14: International sales numbers for BEVs in 2018

Model	Germany	Total Europe	Share Germany	Rank Germany	Austria	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Greece	Ireland	Italy	Netherlands	Norway	Poland	Portugal	Romania	Russia	Slovakia	Slovenia	Spain	Sweden	Switzerland	UK
Ampera	384	2,380	0.16	3	3	0	0	0	0	0	0	0	0	0	860	920	0	0	0	0	0	0	0	0	213	0
B-Klasse	80	338	0.24	3	21	83	0	0	0	0	0	0	0	20	100	6	0	0	0	0	0	0	0	26	0	2
C-Zero	102	1,426	0.07	5	32	28	0	0	0	0	746	0	0	108	29	146	0	159	0	0	1	0	42	0	33	0
e-Niro	18	373	0.05	4	17	0	0	0	0	0	205	0	0	0	0	34	0	0	0	0	0	0	0	99	0	0
forfour	3,654	5,359	0.68	1	19	0	0	0	0	3	321	0	0	158	152	53	0	126	0	0	0	0	691	0	0	182
fortwo	3,045	7,072	0.43	1	137	0	0	0	0	8	1,278	0	0	1,049	100	189	0	220	0	0	0	0	751	0	0	295
Golf	5,722	20,088	0.28	2	1,836	418	0	0	0	128	419	0	75	123	2,223	7,238	0	55	0	0	0	0	266	606	0	979
i3	5,083	24,049	0.21	2	976	715	124	98	5	79	2,422	26	76	356	1,613	5,687	164	370	148	1	34	108	681	803	1,063	3,417
iOn	147	1,639	0.09	3	28	16	0	0	0	0	1,030	0	0	32	23	249	0	2	0	0	0	4	29	0	72	7
IONIQ	1,693	5,881	0.29	2	513	0	0	0	0	0	632	0	0	0	0	2,523	0	74	0	0	0	0	0	0	0	446
Kona	371	2,791	0.13	3	292	0	0	0	0	0	274	0	0	0	551	842	0	15	0	0	0	0	222	0	0	224
Leaf	2,378	38,927	0.06	5	982	977	123	637	60	89	4,670	9	789	1,474	3,369	12,303	269	1,593	53	1	122	106	1,261	1,831	428	5,403
Model S	1,247	16,610	0.075	4	286	535	85	47	2	118	749	0	85	263	5,633	3,633	20	0	0	0	0	7	163	883	837	2,017
Soul	3,289	6,408	0.51	1	79	5	0	0	0	31	650	0	0	25	45	1,469	0	79	0	0	0	0	201	112	0	423
up!	1,011	2,215	0.46	1	72	0	0	0	0	1	234	0	0	69	114	629	0	14	0	0	0	0	0	44	0	27
Zoe	6,357	39,183	0.16	2	1,170	292	8	431	0	55	18,011	0	93	1,030	1,017	3,141	49	1,305	119	0	12	108	1,421	1,663	908	1,993
Focus	17	168	0.10	2	0	0	0	0	0	0	0	0	0	0	0	151	0	0	0	0	0	0	0	0	0	0
i-MiEV	19	328	0.058	3	0	0	0	0	0	0	0	0	0	0	0	205	0	0	0	0	0	0	0	0	104	0

Note: This table shows total sales for all BEVs available in Germany in 2018 across Europe. It also shows the share of European sales that Germany accounts for, and where Germany ranks in sales for each model in Europe.

B Additional Figures

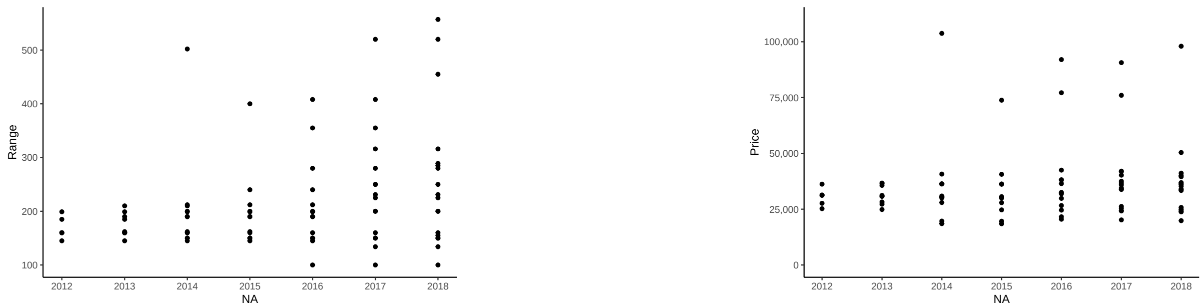

Figure 5: Price and range evolution over time

These tables show price and range for each BEV in the sample for each year.

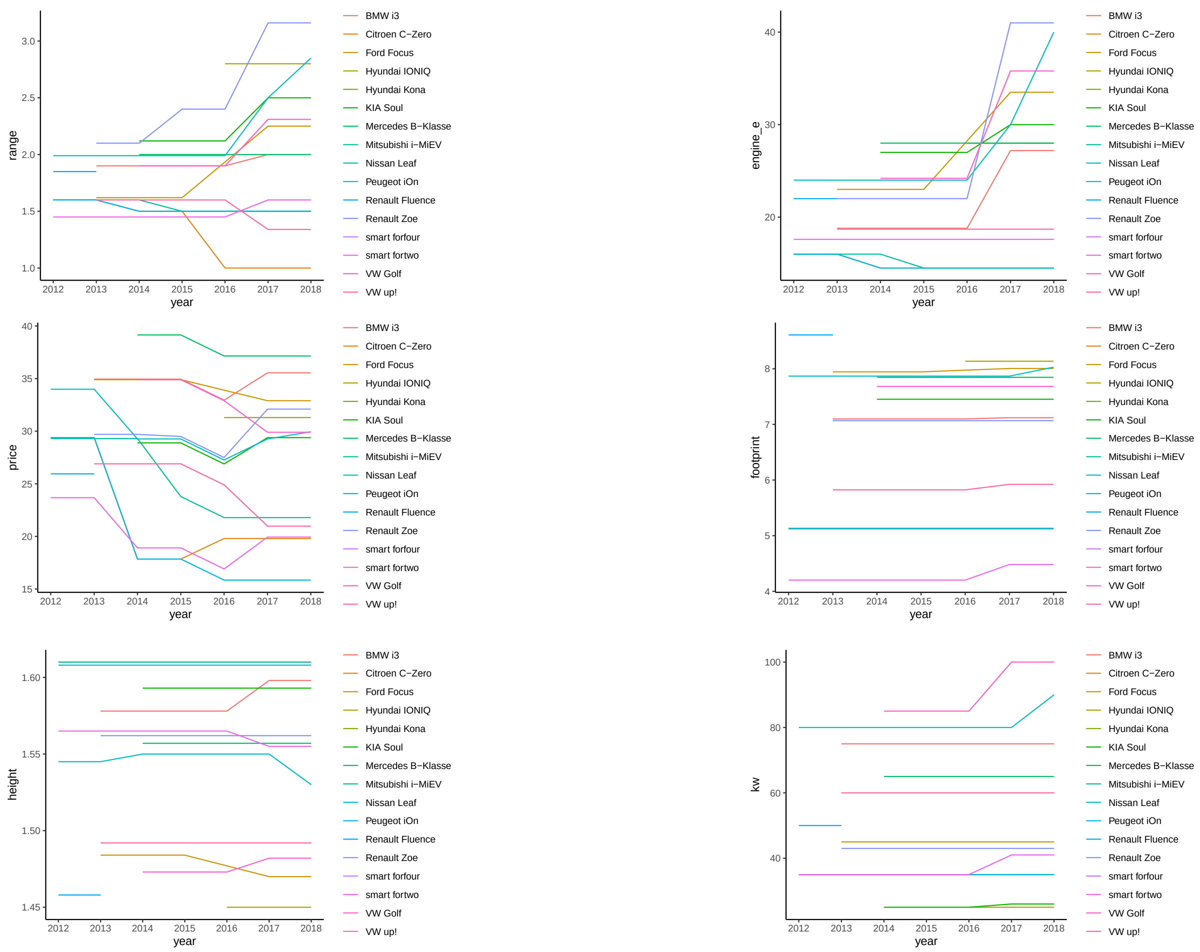

Figure 6: Evolution of selected attributes over time

Note that the Ford Focus was not offered in 2016

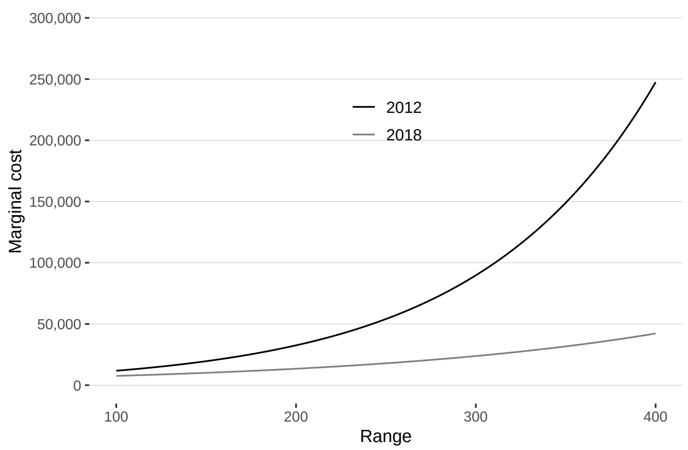

Figure 7: Estimated marginal cost functions for 2012 and 2018

This figure plots hypothetical marginal costs at different range levels in 2012 and 2018.

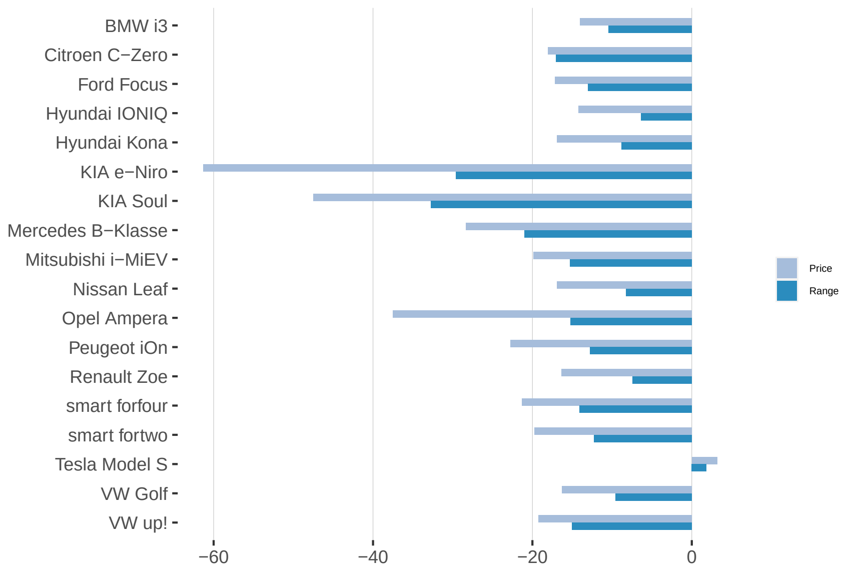

Figure 8: Percentage changes of price and range due to introduction of subsidy

Prices, range levels, marginal costs, markups, and sales are mean values across BEVs.

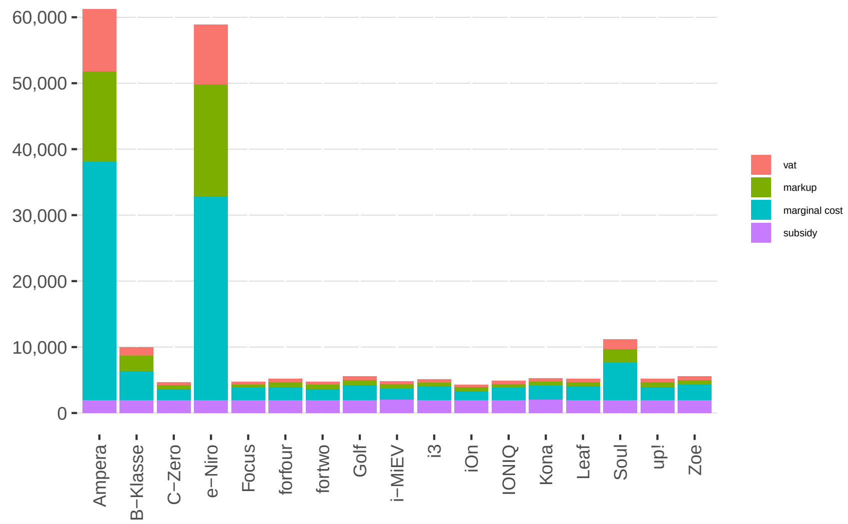

Figure 9: Decomposition of price changes in response to the purchase subsidy.

C Estimation details

C.1 Zero market shares

Approximately 4% of my observations are products with strictly positive national-level sales but zero state-level sales. Zero sales pose a problem in random coefficient demand models, as the estimation procedure is not well defined when zero sales are present. Deleting observations with zero sales from the sample is problematic because it alters the market structure and makes these products unavailable in counterfactual analyses. There exist approaches in the literature to accommodate zero sales in random coefficient demand models.[31] I follow D'Haultfœuille, Durrmeyer, and Février (2019) and use a simple correction of state-level market shares:

$$s^c_{jm} = \frac{q^{obs}_{jm} + 0.5}{\mathcal{M}_m},$$

where q^{obs}_{jm} is the observed quantity sold of product j in a given market and $\mathcal{M}_m$ is the market size in that market. This correction aims to minimize the bias of $\log(s_{jm})$ such that demand parameters can be consistently estimated. D'Haultfœuille et al. (2019) provide an interesting and detailed discussion on this. The zero sales problem is rather small in my sample, given that it only affects approximately 4% of my observations. My results are robust to the use of different corrections (such as replacing $q_{jm} = 0$ with $q_{jm} = 1$, see Appendix I), which I see as evidence that my demand parameters are consistently estimated and lead me to believe that the correction I use is sufficient.

C.2 Estimation of the car demand side

On the demand side, the vector of parameters to be estimated is given by $\theta_d \equiv (\beta^x_i, \beta^r, \alpha)$. I allow for random coefficients on characteristics for which I believe consumer heterogeneity matters: the driving range, an *EV* dummy for battery- and plug-in hybrid vehicles and *Fuel Cost*, measured in €/100 km. The random coefficient on range allows for flexible substitution patterns between EVs with different range levels. The random coefficient on the *EV* dummy allows for flexible substitution between electric cars and combustion engine cars. Obtaining such flexible substitution patterns is crucial for studying the market outcomes of subsidy schemes, as substitution between EVs with different range levels and across engine types drives these outcomes. The random coefficient on *Fuel Cost* allows consumers to have idiosyncratic preferences for a characteristic that proxies the usage cost of cars. Additionally, substantial differences across engine types exist in the fuel cost per 100 km, which renders the substitution patterns between cars of different engine types more flexible. I include a trend in the mean taste for range, possibly capturing taste changes for range over time. In addition, I add several characteristics for which I only estimate the mean taste, including the number of public charging stations per 10,000 inhabitants, fuel cost, footprint, doors, dummies for electric vehicles, a linear time trend, and a dummy if the firm has its headquarters in the state considered.[32] I

[31] Li (2023) uses a Bayesian shrinkage estimator to move market shares away from zero. Gandhi, Lu, and Shi (2022) construct bounds for the conditional expectation of inverse demand and show that their approach works well even when the fraction of zero sales is 95%. Dubé, Hortaçsu, and Joo (2021) use a pairwise-differencing approach to estimate demand parameters.

[32] I introduce the last variable to account for the fact that car companies often register a large number of cars in their home state. Firms do so to comply with emissions regulations or to sell these cars at a discount later. Not accounting for this may introduce a bias, especially for products with small market shares.

also add brand, class, body, and state fixed effects. All remaining unexplained variation is then collected in ξ_{jmt}, which is interacted with the instruments described in the previous section to build moment conditions of the form $E[z^d_{jmt}\xi_{jmt}] = 0$, with z^d_{jmt} as an instrument. Stacking ξ_{jmt} across products and markets into a column vector ξ, I obtain the GMM objective function to be minimized:

$$\min_{\theta_d} \xi(\theta_d)' Z^d W^d Z^{d'} \xi(\theta_d),$$

where Z^d contains the instruments and W^d is a positive definite weighting matrix. I use the two-step efficient GMM estimator, where I use an approximation of the optimal weighting matrix based on an initial set of estimates to recover the final estimated vector of parameters. The estimation algorithm that I use is described in detail in Berry et al. (1995) and Nevo (2001). In the estimation, I account for various numerical issues that recent literature has drawn attention to (Dubé, Fox, and Su (2012), Knittel and Metaxoglou (2014), Brunner, Heiss, Romahn, and Weiser (2017), Conlon and Gortmaker (2020)). First, I approximate the market share integral with 1,000 draws using modified Latin hypercube sampling. Hess, Train, and Polak (2006) and Brunner et al. (2017) show that this method performs very well in random coefficient logit models and provides better coverage than the more frequently used Halton sequences. Second, I set the tolerance level in the contraction mapping of the inner loop to 1e-14 to solve for the demand-side unobservables. A tight tolerance prevents numerical errors from the inner loop from propagating to the outer loop. Third, I use the low-storage BFGS algorithm of NLOPT. Fourth, I initialize the optimization routine from many different starting values to search for a global minimum. Finally, I check first- and second-order conditions at the obtained minimum to ensure the optimizer did not get stuck at a saddle point.

C.3 Estimation of the car supply side

With demand estimates in hand, I can derive implied markups and marginal costs. The vector of parameters to be estimated is $\theta_s = (\psi, \gamma_0, \gamma_1)$. I let the baseline marginal cost depend on several observed characteristics, such as the product's weight, footprint, fuel efficiency, and engine power measured in kilowatts. I also include year, firm, class, and body-fixed effects. All remaining unobserved marginal cost-shifters are then collected in ω_{jt}.

Remember that the marginal cost of range consists of an intercept and a linear time trend to capture the decreasing cost of the lithium-ion cells that are a crucial input for the battery pack, the size of which, in turn, is a main determinant of range. Any unobserved, product-specific cost of additional range is then captured by η_{jt}.

The first-order conditions in (11) and (12) can be solved for the pair of supply-side unobservable vectors ω and η. I then interact them with the instruments described in the previous section to build moment conditions of the form $E[z^s_{jt}\omega_{jt}] = 0$ and $E[z^s_{jt}\eta_{jt}] = 0$. Letting ρ_{jt} = (ω_{jt}, η_{jt}) and stacking across products and markets, I then obtain the GMM objective function to be minimized:

$$\min_{\gamma_0,\gamma_1} \rho(\gamma_0, \gamma_1)' Z^s W^s Z^{s'} \rho(\gamma_0, \gamma_1),$$

where Z^s contains the instruments and W^s is a positive definite GMM weighting matrix. The baseline marginal cost parameters ψ can be concentrated out of the minimization routine, much like the linear mean tastes in the utility function. Note that the number of observations differs on the demand and supply sides. As firms choose price and range at the national level, I have one national market per year t and not m state-level markets per year t on the supply side.

I take into account subsidies as outlined in equations (3)-(4). I do not consider rebates granted by firms for two reasons: The first is that some firms granted larger rebates than they had pledged. I do not observe these rebates. The second reason is that during the sample period, firms also granted substantial rebates on gasoline and especially diesel cars, to a large extent in response to the Volkswagen emissions scandal.[33] The list prices net of government subsidies can be seen as the maximum transaction price, as is the case in most of the literature estimating demand and supply in new car markets.

C.4 Estimation of the charging station entry side

Estimation of the charging station side is straightforward. Once I obtain equation (9), I estimate υ using two-stage least squares. In the estimation, I include national-level subsidies and state-level subsidies. I set the national-level subsidies equal to € 8,000. The vast majority of stations (around 86.7%) in my sample received a subsidy of up to € 3,000 for the installation and of up to € 5,000 for the connection to the grid. In the preferred specification, I also include a linear time trend and state-level controls. In particular, I use the population density (which varies across time) and the surface area of the state (which does not vary across time). I allow the time trend to be different for the states of Berlin, Hamburg, and Bremen. These three states are city-states in which the development of the EV market is likely to be very different from other, less dense, states. I also include a city state dummy to control for unobserved differences between these states and the other states. I also run an alternative specification in which I replace these state-level controls with a state fixed effect which I report along with other robustness checks in Table 12 in Appendix A. I use data from 2015 to 2021 to estimate the station entry side. The reason for this choice is twofold. First, adding later years to the data set offers more cross-sectional and temporal variation in state subsidies and the EV base. Second, I only have information on gasoline and diesel prices starting in late 2014, so I cannot build the gas price instrument for 2012 to 2014.

[33] https://www.handelsblatt.com/unternehmen/industrie/studie-zum-automarkt-wo-es-die-groessten-diesel-rabatte-gibt/22682110.html?protected=true

D Results under simultaneous moves

This section presents results for estimation and subsidy design when assuming a simultaneous move game. In that case, firms just best respond to the charging station side, meaning that we fall back to the standard market share derivatives with respect to price and range.

Table 15: Results under simultaneous moves

Demand/supply for cars			Station entry		
	Coefficient	SE		Coefficient	SE
Demand: Means					
Range	2.274	(0.35)	log(EV base)	0.707	(0.191)
Range x Trend	-0.201	(0.034)	National Subsidies	0.116	(0.021)
log(Charging Stations)	0.373	(0.079)	Local Subsidies	0.022	(0.03)
Fuel Cost	-0.564	(0.039)			
BEV	-10.037	(1.928)			
PHEV	-6.982	(1.824)			
Demand: Obs. Heterogeneity					
Price / Income	-7.112	(0.648)			
Demand: St. Dev.					
BHEV	2.455	(0.891)			
Range	0.326	(0.346)			
Fuel Cost	0.267	(0.017)			
Supply: Range provision					
Intercept	1.171	(0.043)			
Trend	-0.100	(0.009)			
Statistics					
Mean own-price elasticity	-4.043				
Mean own-range elasticity (BEVs)	3.761				
Mean markup (BEVs)	7.629				

Note: Prices, subsidies deflated and in EUR 1,000. Vehicle class-, Body-, Firm-, Year- and State Fixed Effects included on car demand- and supply side. Linear time trend and state demographics included on station entry side.

Table 15 holds the estimation results. As outlined in Section 5, elasticities and markups change. Also, the supply-side results change, even though we can see that they do so only slightly. We still recover the drop in the marginal cost of providing range. Table 16 holds the results for the grid search under simultaneous moves. Akin to Table 6, I report the subsidy schemes that optimize different policy objectives, along with the observed scheme and the case in which there are no subsidies. Table 16 suggests that the results are robust to using this alternative timing assumption. Results in the simultaneous move game are similar to the ones found in Section 6.2. The exact amounts of the subsidies as well as the effects on range, prices, and policy objectives only change slightly. Overall, the conclusions we could draw from Section 6.2 go through.

Table 16: Comparison of subsidy schemes (simultaneous moves)

Scheme	Price	Range	Sales	Stations	CO2	CS	TS
(0, 0, 0)	44,535	293	19,736	9,562	5,198,968	43,321	65,490
(2, 0, 8)	-11,754	-34	+15,025	7,947	-6,763	+157	+254
(2.05, 0, 7.9)	-11,794	-34	+15,186	+7,756	-6,833	+158	+256
(2.3, 0.3, 5.95)	-13,761	-39	+16,384	+4,237	-7,356	+140	+229
(2.3, 0.2, 6.5)	-13,719	-40	+16,391	+5,139	-7,318	+145	+237

E Supply side: details

The first-order conditions in (3) and (4) can be expressed in matrix form. I use the index B for battery electric vehicles and I for other vehicles. I let $\mathcal{J}_B, \mathcal{J}_I$ denote the set of either type of vehicle and J_B, J_I the number of either kind of vehicle on the market. I then define the following matrices:

$$\Delta_p: \ J\text{x}J \text{ matrix with entry } k,l = \begin{cases} \sum_m \phi_{mt} \frac{\partial s_{lmt}}{\partial p_{kt}} \text{ if } k,l \in \mathcal{J}_f \\ 0 \text{ otherwise} \end{cases}$$

$$\Delta_r^B: \ J_B\text{x}J_B \text{ matrix with entry } k,l = \begin{cases} \sum_m \phi_{mt} \frac{\partial s_{lmt}}{\partial r_{kt}} \text{ if } k,l \in \mathcal{J}_f \text{ and } k,l \in \mathcal{J}_B \\ 0 \text{ otherwise} \end{cases}$$

$$\Delta_r^I: \ J_B\text{x}J_I \text{ matrix with entry } k,l = \begin{cases} \sum_m \phi_{mt} \frac{\partial s_{lmt}}{\partial r_{kt}} \text{ if } k,l \in \mathcal{J}_f,\ l \in \mathcal{J}_I \text{ and } k \in \mathcal{J}_B \\ 0 \text{ otherwise} \end{cases}$$

The system of first-order conditions can then be expressed as

$$\begin{cases} \mathbf{s} + (\mathbf{p} + \boldsymbol{\lambda} - \mathbf{mc})\Delta_p = 0 & (11) \\ -\dfrac{\partial \mathbf{mc}^B}{\partial \mathbf{r}^B}\mathbf{s}^B + \Delta_r^B(\mathbf{p}^B + \boldsymbol{\lambda}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I + \boldsymbol{\lambda}^I - \mathbf{mc}^I) = 0, & (12) \end{cases}$$

where $\mathbf{s}$ is the vector of market shares, $\mathbf{p}$ is the vector of prices, $\boldsymbol{\lambda}$ the subsidy vector, $\mathbf{mc}$ the marginal costs vector and $\mathbf{r}$ the vector of range levels. This expression makes apparent that the introduction of a (flat) subsidy is equivalent to a marginal cost decrease from the viewpoint of the firm.

Having a functional form for marginal costs allows me to express the equilibrium levels of price and range in matrix form. Let $\mathbf{c}_0 \equiv \mathbf{w}'\boldsymbol{\psi} + \boldsymbol{\omega}$ and $\mathbf{c}_1 \equiv (\gamma_0 + \gamma_1\mathbf{t} + \boldsymbol{\eta})$. Then, the equilibrium price and range are

$$\begin{cases} \mathbf{p} = \mathbf{mc} + \Delta_p^{-1}\mathbf{s} & (13) \\ \mathbf{r} = \dfrac{1}{\mathbf{c_1}} \log\left(\dfrac{\Delta_r^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I - \mathbf{mc}^I)}{\mathbf{s}^B\mathbf{c}_1}\right) - \dfrac{\mathbf{c}_0}{\mathbf{c}_1} & (14) \end{cases}$$

F Counterfactual details

F.1 Procedure

This section presents details on the counterfactual procedure.

Having estimates of price and range semi-elasticities, a system of first-order conditions (FOCs) for prices and range levels, and an estimate of the marginal cost of providing range, as well as the charging station entry equation, I can compute the new equilibrium vectors of price and range and the new equilibrium entry of charging stations. I employ an iterative algorithm to find this new equilibrium $(\mathbf{p}, \mathbf{r}, \mathbf{d})$. I proceed as follows:

1. I start with a vector of prices $\boldsymbol{p}^l$, ranges $\boldsymbol{r}^l$, and charging stations $\boldsymbol{d}^l$.

2. Update price and range vectors. At iteration h,

(a) Compute a new price vector using the price FOC given by equation (13). Take a small step towards the simulated price vector: $\boldsymbol{p}^{h+1} = \alpha \boldsymbol{p}^* + (1-\alpha)\boldsymbol{p}^h$, with α small.

(b) Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{r}^h$

(c) Compute a new range vector using the range FOCs given by equation (14). Take a small step towards the simulated range vector: $\boldsymbol{r}^{h+1} = \alpha \boldsymbol{r}^* + (1-\alpha)\boldsymbol{r}^h$, with α small.

(d) Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{r}^{h+1}$

(e) Let $\text{diff}_{max} = \max(\text{diff}_p^h, \text{diff}_r^h)$, where $\text{diff}_p^h = \max|\mathbf{p}^{h+1} - \mathbf{p}^h|$ and $\text{diff}_r^h = \max|\mathbf{r}^{h+1} - \mathbf{r}^h|$. If $\text{diff}_{max} \geq \epsilon^c$ with ϵ^c being some convergence criterion, go back to step (a). If $\text{diff}_{max} < \epsilon^c$, extract $(\mathbf{p}^{h+1}, \mathbf{r}^{h+1})$ to be the new equilibrium vector of prices and range levels $\boldsymbol{p}^{l+1}$ and $\boldsymbol{r}^{l+1}$.

3. Update charging stations by iterating on equation (8) until convergence. Extract the new charging station vector $\boldsymbol{d}^{l+1}$.

4. Compute $\text{diff}_{max}^l = \max(\text{diff}_p^l, \text{diff}_r^l), \text{diff}_d^l)$. If $\text{diff}_{max}^l >= \epsilon^o$, go back to step 2. If $\text{diff}_{max}^l < \epsilon^o$, $\boldsymbol{p}^{l+1}, \boldsymbol{r}^{l+1}, \boldsymbol{d}^{l+1}$ is the new equilibrium vector of prices, ranges, and charging stations.

I restrain the values that the range can take in counterfactuals. First, I put a floor of 100km, which is the lowest range I observe for BEVs throughout the sample period. Second, I bound range from above in the following way: First, I define c_{1min} to be the lowest marginal cost of providing range in 2018: $c_{1min} = \min_{j \in J_{BEV,2018}}(c_{1j})$. I then define the maximum attainable range in 2018 for BEV j to be $r_{max,j} \equiv \big(\log(mc_j) - c_{0j}\big)/(c_{1min} \times 1.2)$. I find that this procedure converges to the same equilibrium vector of prices levels, range levels, and charging stations even when I start from different starting values in different counterfactual settings. I take this feature as a sign that there exists a unique counterfactual equilibrium. Altering the ordering of the price and range updating does not change the results, also giving me confidence that the counterfactual results that I find are robust to the specific details of the algorithm and different starting values. The fact that firms choose only the range of BEVs means that the number of additional FOCs to iterate in addition to the price FOCs is small. This factor contributes to the good convergence properties of the algorithms. I perform all counterfactuals for 2018.

F.2 Details on grid search

To find the budget-equivalent values for $\boldsymbol{\lambda}$, I use the following procedure: At a given budget B, I search for values of $\boldsymbol{\lambda}$ that satisfy the budget constraint. I employ a grid search where at each candidate value $\tilde{\boldsymbol{\lambda}}$, I solve for the counterfactual equilibrium vector of prices and ranges as outlined in Appendix F and compute the total cost of the scheme. If the cost is either above or below B, I discard the candidate value, and if the cost is equal to B (up to a small tolerance), I keep it. For each candidate point, I compute the mean price and range of BEVs, the quantity sold of BEVs, consumer surplus[34], and fleet emissions. To calculate fleet emissions, I rely on data that gives me the average distance driven by fuel type coming from a survey conducted by

[34] Consumer surplus is computed using the log-sum formula: $CS_t = \sum_m \phi_{mt} \sum_i w_i \frac{log(1+\sum_j \exp(\delta_{jmt}+\mu_{ijmt}))}{\alpha_i}$.

the German Federal Highway Research Institute (Bäumer, Hautzinger, Pfeiffer, Stock, Lenz, Kuhnimhof, and Köhler, 2017).[35]

Note that in the computation of fleet emissions, I assume that BEVs' CO2 emissions are equal to zero. Obviously, this assumption is only true if they run exclusively on electricity generated from renewable sources. The assumption is unrealistic in a country such as Germany, where an important part of electricity generation comes from CO2-intensive coal-fired plants. However, there are three reasons why this approach is justified. The first is that it serves as a useful benchmark since it measures the maximum amount by which fleet emissions can decrease. The second is that the main reason why policymakers see electric vehicles as a key instrument in making the transport sector emission-free is that electricity generation itself is being decarbonized. Decarbonized electricity generation means that BEVs will eventually be emission-free, making it a useful benchmark to think of them as zero-emission vehicles. The third reason is that assuming non-zero CO2 emissions from BEVs requires ad hoc assumptions on the electricity mix used and driving behavior.

G The role of internalizing spillovers on price and range choices

In the estimation of the model, I find that ignoring indirect network effects leads to markups that are 19% higher on average and that BEVs act as complements in both price and range. In the first set of counterfactuals that I perform, I take a closer look at the relationship between indirect network effects and firms' price and range choices. In particular, I am interested in how the complementarity between BEVs affects market outcomes. I consider two scenarios. In the first scenario, I assume firms do not internalize the effect of their price and range choices on any other EV, not even the EVs in their product portfolio. This scenario amounts to modifying the matrices Δ_p and Δ_r^B in equations (11) and (12). Specifically, I set each entry $(j, k),\ j \neq k$ in (11) and (12) to zero if row j and row k correspond to an EV. Note that doing so is different from assuming single-product firms as firms still internalize diverted sales towards own-firm combustion cars. In the second scenario, I assume firms internalize the effects of their price and range decisions on all other EVs in the market. This scenario also amounts to modifying the matrices Δ_p and Δ_r^B in equations (11) and (12). Specifically, I set each entry (j, k) in (11) and (12) to one if row j and row k correspond to an EV. Note that doing so is different from assuming a complete merger to monopoly in the car market as firms still only internalize diverted sales towards own-firm combustion cars and not towards combustion cars produced by other firms. Given the vast majority of new car sales still comes from combustion cars in 2018, assuming a full merger to monopoly would likely entail large coordinated effects that would pollute the effect of merely assuming full internalization on rival firm EVs.

The results are in Table 17. We can see that in the scenario in which firms do not internalize the effect of their price and range choices on any other EV (column "No internalization"), BEVs would on average be more expensive and have a higher range. Sales of BEVs would be lower and fewer charging stations would enter. These results suggest that complementarities in price and range choices lead to BEVs that are cheaper, but also have a slightly lower range. These cheaper, lower-range BEVs generate a large number of extra sales and also spur charging station entry. On the other hand, we can see in the last column that when firms internalize the effect of their price and range choices on all other EVs in the market, BEVs are on average substantially cheaper and have a much lower range. However, these cheap, low-range BEVs generate large

[35] I compute fleet emissions as $\sum_j \text{CO2}_j\ q_j\ \text{usage}_j$, with CO2_j being the CO2 emissions of car j, measured in g/km, q_j being the quantity sold of car j, and usage_j the annual amount driven in km.

Table 17: Market outcomes with different market structures

	Data	No internalization	Full internalization
Price	34,782	+3,560	-5,687
		(-1,639, +7,903)	(-12,422, +3,674)
Range	259	+10	-27
		(-13, +21)	(-119, -4)
MC	21,774	+1,816	-2,836
		(-1,287, +4,718)	(-6,746, +2,027)
Markup	7,361	+1,176	-1,943
		(-139, +2,065)	(-3,924, +954)
Sales	34,761	-1,789	+10,930
		(-5,073, +2,854)	(-24, +37,137)
Stations	17,509	-208	+1,041
		(-3,089, +4,880)	(-1,854, +8,029)
Consumer Surplus	49,250	-29	+132
		(-3,022, +4,078)	(-2,931, +4,376)
CO2 emissions	5,192,205	+404	-2,806
		(-1,510, +2,255)	(-13,205, +1,232)

Note: Table gives differences to observed outcomes with 90% C.I. in parentheses. Prices, range levels, marginal costs, markups, and sales are mean values across BEVs.

additional sales and strong charging station entry. Overall, consumer surplus would increase by around €200 million in this case. However, much of the increase in consumer surplus comes from increased substitution from the outside option. The rest of the consumer surplus increase comes from the fact that EVs become substantially cheaper, and the fact that there are more charging stations available. Interestingly, firms have an incentive to reduce the range of their cars when internalizing indirect network effects. One reason for this may be that consumers have a relatively low willingness to pay for range. Another reason is the indirect network effects at play: Reducing the price of BEVs induces more charging station entry. This increase in charging stations makes it possible for firms to reduce range and generate additional sales by further reducing the price. The indirect network effects strengthen the incentives of firms to reduce price and range.

H Alternative model with range-charging station interaction

This section presents an alternative version of the demand and supply model where I allow for an interaction term between EV driving range and charging stations. In order to identify this interaction term, I include the natural logarithm of range (measured in km) in the demand. In particular, the utility that consumer i enjoys from purchasing one of the products $j = 1, \ldots, J$ is

$$u_{ijmt} = \underbrace{\beta_i^b BEV_j + \beta_i^p PHEV_j + \beta^r log(r_{jt}) + \beta^d log(d_{jmt}) + \beta^{rd} log(r_{jt}) log(d_{jmt})}_{\text{only EVs}}$$
$$\underbrace{-\alpha \frac{p_{jt}}{y_{imt}} + x_{jmt}\beta_i^x + \xi_{jmt} + \varepsilon_{ijmt}}_{\text{all cars}},$$

Note that while range and charging stations are likely to be substitutes to some extent, the ultimate extent to which this is the case will depend on an individual's driving needs, their home and/or work place charging availability, and other factors. Including an interaction term between range and charging stations is hence a rather crude way of capturing the interactions between these two variables.

The estimation results in Table 18 suggest that range and charging stations are substitutes, with the valuation of range being a decreasing function of the number of charging stations and vice versa. Introducing the log of charging stations has implications for the first-order conditions, and the estimates of c_1, the term pre-multiplying range in the marginal cost function, because the level of range is now measured in kilometers instead of 100 kilometers. I obtain similar estimates of the marginal cost of providing range, however.

Table 18: Estimation results with interaction

Demand/supply for cars			**Station entry**		
	Coefficient	SE		Coefficient	SE
Demand: Means					
log(Range)	1.877	(0.232)	log(EV base)	0.707	(0.191)
log(Charging Stations)	0.555	(0.198)	National Subsidies	0.116	(0.021)
log(Range) x log(Charging Stations)	-0.100	(0.039)	Local Subsidies	0.022	(0.030)
Fuel Cost	-0.611	(0.039)			
BEV	-13.182	(2.923)			
PHEV	-10.940	(2.878)			
Demand: Obs. Heterogeneity					
Price / Income	-7.352	(0.627)			
Demand: St. Dev.					
BHEV	1.466	(1.834)			
Fuel Cost	0.289	(0.017)			
Supply: Range provision					
Intercept	0.00510	(0.00035)			
Trend	-0.00044	(0.00008)			
Statistics					
Mean own-price elasticity	-4.163				
Mean own-range elasticity (BEVs)	1.399				
Mean markup (BEVs)	7.614				

Note: Prices, subsidies deflated and in EUR 1,000. Vehicle class-, Body-, Firm-, Year- and State Fixed Effects included on car demand- and supply side. Linear time trend and state demographics included on station entry side.

In Table 19 we see that the trade-off between maximizing EV sales, maximizing consumer and total surplus, and minimizing CO2 emissions persists. There are slight changes to the type of subsidy schemes that optimize different policy goals. Instead of focusing on subsidizing charging station entry, consumers now prefer a scheme that balances incentivizing charging station entry and incentivizing range provision. The EV sales-maximizing scheme looks very similar to the one in the main specification, with the policymaker having an incentive to focus most of the spending on flat purchase subsidies. To minimize CO2 emissions, the policymaker should increase the flat part of the purchase subsidy and decrease the charging station subsidy. Again, this scheme looks very similar to before. Overall, price and range adjustments are less strong compared to the model in the main part of the paper. This is because shifting spending to purchase subsidies reduces charging station entry, which increases consumers' willingness to pay for range and hence increases firms' incentives to provide it, limiting the scope for large range reductions and accompanying price reductions.

I Robustness to alternative corrections

Table 20 shows estimates of key demand parameters under different corrections for observations with zero market shares. The column *Min bias* holds the results from the correction

Table 19: Comparison of subsidy schemes: range-station interaction

Scheme	Price	Range	Sales	Stations	CO2	CS	TS
(0, 0, 0)	36035	249	25733	9570	5196956	43198	64748
(2, 0, 8)	-3,253	-17	+9,028	+7,939	-4,751	+87	+183
(3.15, 0, 4)	-4,358	+13	+14,656	+1,850	-7,374	+107	-55
(3.25, 0, 2.85)	-4,388	+15	+15,062	+797	-7,530	+107	-57
(3.25, 0, 2.85)	-4,388	+15	+15,062	+797	-7,530	+107	-57

employed in the paper that follows D'Haultfœuille et al. (2019). The second column (*Laplace*) uses a correction based on Laplace's rule of succession that is used in Gandhi, Lu, and Shi (2013). It consists of replacing market shares by $\tilde{s_{jmt}} = \frac{\mathcal{M}_{mt}s_{jmt}+1}{\mathcal{M}_{mt}s_{jmt}+J_{mt}+1}$, with J_{mt} the number of products in market mt. Finally, column 3 (*Naive*) uses a naive correction where quantities of zero sales observations are assumed to be 1. We can see that the estimates barely differ across the different corrections, leading me to conclude that the prevalence of zero sales do not pose a serious threat in my estimation.

Table 20: Estimates of key parameters under alternative corrections for zero market shares

	Min bias	**Laplace**	**Naive**
Mean Utility			
Range	2.274	2.175	2.256
	(0.350)	(0.330)	(0.340)
Range x Trend	-0.201	-0.19	-0.193
	(0.034)	(0.032)	(0.033)
Charging Stations	0.373	0.349	0.373
	(0.079)	(0.076)	(0.078)
Fuel Cost	-0.564	-0.552	-0.571
	(0.039)	(0.037)	(0.038)
BEV	-10.037	-9.626	-10.204
	(1.928)	(1.87)	(1.921)
PHEV	-6.982	-6.767	-7.229
	(1.824)	(1.772)	(1.808)
Obs. Heterogeneity			
Price / Income	-7.112	-6.904	-7.263
	(0.648)	(0.608)	(0.646)
Standard Dev.			
BHEV	2.455	2.450	2.579
	(0.891)	(0.864)	(0.861)
Range	0.326	0.299	0.303
	(0.346)	(0.349)	(0.359)
Fuel Cost	0.267	0.262	0.269
	(0.017)	(0.016)	(0.017)

Note: Standard errors in parentheses.

J Estimated price elasticities in selected papers

Table 21 presents estimates of price elasticities from several papers using a similar structural model of demand to mine.

Table 21: Estimated price elasticities of selected papers

Author(s)	Price elasticity
Beresteanu and Li (2011)	-10.91
Berry et al. (1995)[1]	-3.928
Berry et al. (1995)[2]	-3.461
Li (2023)	-2.732
Klier and Linn (2012)	-2.6
Pavan (2017)	-2.85
Reynaert and Sallee (2021)	-5.45
Springel (2021)[3]	[-1, -1.5]
Thurk (2018)	-3.6
Grieco et al. (2023)[4]	-5.36

Own estimated price elasticity: -4.043
[1] Conlon and Gortmaker (2020) replication
[2] Conlon and Gortmaker (2020) own procedure
[3] Range of elasticities for EVs
[4] For 2015

K A model of quality provision

K.1 Monopoly

In this section, I outline a model of quality provision by a monopolist. This model helps to understand the forces that determine how price and quality adjust to the introduction of a subsidy or a decrease in the marginal cost of quality provision. Note that what I call quality in this model can, in principle, be any product characteristics, such as driving range.

Set-up

Let us consider a monopolist who chooses price (p) and quality (q) of a single product sold to final consumers.[36] In my application, q would be the driving range of a car. The demand function $s(p, q)$ is increasing in quality, decreasing in price, and is twice differentiable. Cost is an increasing function of quality and is denoted $c(q)s(p, q)$. A social planner subsidizes the product with a subsidy denoted by λ, possibly to increase the diffusion of the product. This scheme mirrors the type of subsidy for electric vehicles employed in countries such as Germany.

Quality choice

The monopolist maximizes its total profits given by $\pi(p, q)$. His optimization problem is given by

$$\max_{p,q} \pi(p, q) \equiv \ (p + \lambda - c(q)) \ s(p, q)$$

[36]The set-up slightly differs from Spence (1975) and Sheshinski (1976) where the monopolist's choice variables are quality and quantity.

and the first-order conditions of the monopolist are given by

$$\begin{aligned}
\text{[p]:} \quad & \pi_p \equiv s(p,q) + (p+\lambda-c)\frac{\partial s(p,q)}{\partial p} = 0 \\
\text{[q]:} \quad & \pi_q \equiv -c_q s(p,q) + (p+\lambda-c)\frac{\partial s(p,q)}{\partial q} = 0.
\end{aligned}$$

For the price, we recover the standard optimal markup formula. For quality, the formula looks similar. The firm faces a trade-off: It can increase quality to expand sales. However, doing so is costly and leads to a smaller margin. To see how the monopolist chooses quality in equilibrium, we can plug the price FOC into the quality FOC and re-arrange to find

$$c_q = \frac{\partial s(p,q)/\partial q}{|\partial s(p,q)/\partial p|}, \tag{15}$$

where c_q is the marginal cost of providing quality $\frac{\partial c(q)}{\partial q}$ The monopolist sets quality such that the marginal cost of providing quality is equal to the absolute value of the ratio of semi-elasticities of quality and price. The larger the fraction on the right-hand side of equation (15), the larger the level of quality provided in equilibrium.

The effect of a subsidy

What happens when the policymaker introduces a subsidy? If quality cannot adjust, we expect the monopolist to pass on the subsidy by lowering the price. The extend of this pass-through depends on the curvature of the demand curve. The more elastic the demand curve, the higher the amount of pass-through. If both the price and quality can adjust, there is no clear-cut answer to how the monopolist will react. Differentiating the system of first–order conditions gives

$$\begin{bmatrix} \frac{dp}{d\lambda} \\ \frac{dq}{d\lambda} \end{bmatrix} = \begin{bmatrix} \pi_{pp} & \pi_{pq} \\ \pi_{pq} & \pi_{qq} \end{bmatrix}^{-1} \begin{bmatrix} -\pi_{p\lambda} \\ -\pi_{q\lambda} \end{bmatrix},$$

where π_{mn} denotes the second order derivative of the monopolist's profit function respect to m and n, with $m, n \in \{p, q\}$ and where

$$\begin{aligned}
\pi_{pp} &= 2s_p + s_{pp}(p+\lambda-c) \\
\pi_{qq} &= -c_{qq}s - 2c_q s_q + s_{qq}(p+\lambda-c) \\
\pi_{pq} &= s_q + (p+\lambda-c)s_{pq} - c_q s_p \\
\pi_{p\lambda} &= s_p, \quad \pi_{q\lambda} = s_q.
\end{aligned}$$

This gives

$$\begin{aligned}
\frac{dp}{d\lambda} &= \frac{1}{\Delta}\Big(\pi_{pq}\pi_{q\lambda} - \pi_{qq}\pi_{p\lambda}\Big) \\
\frac{dq}{d\lambda} &= \frac{1}{\Delta}\Big(\pi_{pq}\pi_{p\lambda} - \pi_{pp}\pi_{q\lambda}\Big),
\end{aligned}$$

where $\Delta \equiv \pi_{pp}\pi_{qq} - \pi_{pq}^2 > 0$ from the second order conditions of having a global maximum. The SOCs further require $\pi_{pp} < 0$ and $\pi_{qq} < 0$. Note that we also have $\pi_{p\lambda} < 0$ and $\pi_{q\lambda} > 0$. If $\pi_{pq} < 0$, meaning price and quality are strategic substitutes, we have $\frac{dp}{d\lambda} < 0$ and $\frac{dq}{d\lambda} > 0$.

In the case where $\pi_{pq} > 0$, things become more ambiguous. Note that we can write

$$\frac{dp}{d\lambda} = \frac{1}{\Delta}\Big(\pi_{pq}s_q - \pi_{qq}s_p\Big)$$
$$\frac{dq}{d\lambda} = \frac{1}{\Delta}\Big(\pi_{pq}s_p - \pi_{pp}s_q\Big),$$

We can then conclude that

$$\text{sign}\Big(\frac{dp}{d\lambda}\Big) = \text{sign}\Big(\Big|\frac{s_q}{\pi_{qq}}\Big| - \Big|\frac{s_p}{\pi_{pq}}\Big|\Big)$$
$$\text{sign}\Big(\frac{dq}{d\lambda}\Big) = \text{sign}\Big(\Big|\frac{s_p}{\pi_{pp}}\Big| - \Big|\frac{s_q}{\pi_{pq}}\Big|\Big)$$

The effect of a subsidy on quality and price depends on the relative magnitudes of the price and quality semi-elasticities, s_p and s_q, and the marginal cost of providing quality c_q. Moreover, we can rule out the case $\pi_{p\lambda} > 0$ and $\pi_{q\lambda} < 0$. To see see why, note that this case would imply $\frac{\pi_{pq}}{\pi_{pp}} < \frac{s_q}{s_p} < \frac{\pi_{qq}}{\pi_{pq}}$ which violates the second order conditions.

K.2 Multi-product oligopoly

In this section I show how the main insights obtained in the monopoly case generalize to a multi-product oligopoly setting. The fact that there are cannibalization effects within a firm's product portfolio and the fact that products are differentiated within and across the product portfolio will influence the effect of a subsidy on price and quality but not alter the main conclusions. To see why, let us consider the following setting: There are $j = 1, \dots J$ products in a market. Consumers care about the quality of a subset of products $j \in \mathcal{B}$ and do not have any preferences over the quality of the remaining products $j \in \mathcal{I}$.[37] The social planner puts a subsidy on products in $\mathcal{B}$ but not on those in $\mathcal{I}$. Let us look at the firm f's profit maximization problem:

$$\max_{p_f, q_f} \pi_f = \sum_{k \in \mathcal{J}_f \cap k \in \mathcal{B}} (p_k + \lambda - c(q_k))s_k(p,q) + \sum_{l \in \mathcal{J}_f \cap k \in \mathcal{I}} (p_l - c(q_l))s_l(p,q),$$

where p_f and q_f denote the own-firm vectors of price and quality, respectively, p and q the price and quality vectors of all firms in the market and J_f the portfolio of firm-f products. The FOCs

[37]Think of the market for cars: The range of electric cars is a proxy for quality and costly to provide. Consumers do not care about the range of diesel or gasoline cars as it is sufficiently high and firms do not give it first-order importance when making their strategic decisions.

for product one are then given by

$$
\begin{aligned}
&[p_1]: \quad \pi_{fp_1} \equiv \\
&s_1 + \sum_{k \in \mathcal{J}_f \cap k \in \mathcal{B}} (p_k + \lambda - c(q_k)) \frac{\partial s_k}{\partial p_1} + \sum_{l \in \mathcal{J}_f \cap k \in \mathcal{I}} (p_l - c(q_l)) \frac{\partial s_l}{\partial p_1} = 0 \\
&[q_1]: \quad \pi_{fq_1} \equiv \\
&- c_{q_1} s_1 + \sum_{k \in \mathcal{J}_f \cap k \in \mathcal{B}} (p_k + \lambda - c(q_k)) \frac{\partial s_k}{\partial q_1} + \sum_{l \in \mathcal{J}_f \cap k \in \mathcal{I}} (p_l - c(q_l)) \frac{\partial s_l}{\partial q_1} = 0
\end{aligned}
$$

The second-order derivatives of the profit function will depend not only on the effect of own price and quality on own demand, but also on the demand of the other own-firm products. Finally, they depend on rival product prices and quantities through the demand function.

Increase of subsidy for a single product

In the case where the subsidy is only increased for a single product, say product 1, we get

$$
\begin{aligned}
\frac{dp_1}{d\lambda} &= \frac{1}{\Delta}\Big(\pi_{fp_1q_1}\pi_{fq_1\lambda} - \pi_{fq_1q_1}\pi_{fp_1\lambda}\Big) \\
\frac{dq_1}{d\lambda} &= \frac{1}{\Delta}\Big(\pi_{fp_1q_1}\pi_{fp_1\lambda} - \pi_{fp_1p_1}\pi_{fq_1\lambda}\Big),
\end{aligned}
$$

meaning that the general results from the previous section go through: The signs of $\frac{dp_1}{d\lambda}, \frac{dq_1}{d\lambda}$ depend on whether p, q are strategic substitutes or complements. They also still depend on the marginal cost of providing quality as well as the relative magnitudes of $\pi_{fp_1\lambda}$ and $\pi_{fq_1\lambda}$ that themselves still depend on s_p and s_q.

Increase in the subsidy for all products in $\mathcal{B}$

Things become more complicated when we consider an increase on the subsidy of all products in $\mathcal{B}$. We now need to differentiate $J + J_{\mathcal{B}}$ first–order conditions ($J_{\mathcal{B}}$ being the cardinality of $\mathcal{B}$). In essence, the effect of price and quality on the FOC of all other products now needs to be taken into account as well.
Let J denote the cardinality of all products, $J_{\mathcal{B}}$ the cardinality of those products with endogenous quality and $f(j)$ the firm of product j. Then, we have the following system of FOCs with $J + J_q$ equations:

$$
\begin{aligned}
&[p_1]: \quad \pi_{f(1)p_1} \equiv s_1 + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial p_1} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial p_1} = 0 \\
&\vdots \\
&[p_J]: \quad \pi_{f(J)p_J} \equiv s_J + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial p_J} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial p_J} = 0 \\
&[q_1]: \quad \pi_{f(1)q_1} \equiv -c_{q_1} s_1 + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial q_1} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial q_1} = 0 \\
&\vdots \\
&[q_{J_{\mathcal{B}}}]: \quad \pi_{f(J_{\mathcal{B}})q_{J_{\mathcal{B}}}} \equiv -c_{q_{J_{\mathcal{B}}}} s_{J_{\mathcal{B}}} + \sum_{k \in \mathcal{J}_{f(J_{\mathcal{B}})} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial q_{J_{\mathcal{B}}}} + \sum_{l \in \mathcal{J}_{f(J)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial q_{J_{\mathcal{B}}}} = 0
\end{aligned}
$$

The total differentiation of this system yields

$$\begin{bmatrix} \frac{dp_1}{d\lambda} \\ \vdots \\ \frac{dp_J}{d\lambda} \\ \frac{dq_1}{d\lambda} \\ \vdots \\ \frac{dq_{J_\mathcal{B}}}{d\lambda} \end{bmatrix} = \begin{bmatrix} \pi_{f(1)p_1p_1} & \cdots & \pi_{f(J)p_Jp_1} & \pi_{f(1)q_1p_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1p_J} & \cdots & \pi_{f(J)p_Jp_J} & \pi_{f(1)q_1p_J} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_J} \\ \pi_{f(1)p_1q_1} & \cdots & \pi_{f(J)p_Jq_1} & \pi_{f(1)q_1q_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J)p_Jq_{J_\mathcal{B}}} & \pi_{f(1)q_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_{J_\mathcal{B}}} \end{bmatrix}^{-1} \begin{bmatrix} -\pi_{f(1)p_1\lambda} \\ \vdots \\ -\pi_{f(J)p_J\lambda} \\ -\pi_{f(1)q_1\lambda} \\ \vdots \\ -\pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}\lambda} \end{bmatrix}, \tag{16}$$

where, for instance,

- $\pi_{f(1)p_1p_1} = 2\frac{\partial s_1}{\partial p_1} + \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial p_1^2} + \sum_{l\in\mathcal{J}_{f(1)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial p_1^2}$
- $\pi_{f(J)p_Jp_1} = \frac{\partial s_J}{\partial p_1} + \frac{\partial s_J}{\partial p_1}\mathbf{1}\{1,J\in f(J)\} + \sum_{k\in\mathcal{J}_{f(J)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial p_J\partial p_1} + \sum_{l\in\mathcal{J}_{f(J)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial p_J\partial p_1}$
- $\pi_{f(1)p_1q_1} = -c_{q_1}\frac{\partial s_1}{\partial p_1} + \frac{\partial s_1}{\partial q_1} + \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial p_1\partial q_1} + \sum_{l\in\mathcal{J}_{f(1)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial p_1\partial q_1}$
- $\pi_{f(1)p_1q_{J_\mathcal{B}}} = -c_{q_{J_\mathcal{B}}}\frac{\partial s_{J_\mathcal{B}}}{\partial p_1}\mathbf{1}\{1,J_\mathcal{B}\in f(1)\} + \frac{\partial s_1}{\partial q_{J_\mathcal{B}}} + \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial p_1\partial q_{J_\mathcal{B}}} + \sum_{l\in\mathcal{J}_{f(1)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial p_1\partial q_{J_\mathcal{B}}}$
- $\pi_{f(1)q_1q_1} = -c_{q_1q_1}s_1 - 2c_{q_1}\frac{\partial s_1}{\partial q_1} + \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial q_1^2} + \sum_{l\in\mathcal{J}_{f(1)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial q_1^2}$
- $\pi_{f(1)q_1q_{J_\mathcal{B}}} = -c_{q_{J_\mathcal{B}}}\frac{\partial s_{J_\mathcal{B}}}{\partial q_1}\mathbf{1}\{1,J_\mathcal{B}\in J_f\} - c_{q_1}\frac{\partial s_1}{\partial q_{J_\mathcal{B}}} + \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} (p_k+\lambda-c_k)\frac{\partial^2 s_k}{\partial q_1\partial q_{J_\mathcal{B}}} + \sum_{l\in\mathcal{J}_{f(1)}\cap l\in\mathcal{I}} (p_l-c_l)\frac{\partial^2 s_l}{\partial q_1\partial q_{J_\mathcal{B}}}$
- $\pi_{p_1\lambda} = \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} \frac{\partial s_k}{\partial p_1}$
- $\pi_{q_1\lambda} = \sum_{k\in\mathcal{J}_{f(1)}\cap k\in\mathcal{B}} \frac{\partial s_k}{\partial q_1}$

It is no longer possible to simply pin down the effects of the subsidy on whether or not p, q are strategic complements, nor on the relative magnitudes of $\pi_{fp_1\lambda}$ and $\pi_{fq_1\lambda}$ and the marginal cost of providing quality. First off, however, the entries $\pi_{fp_jp_j}$ and $\pi_{fq_jq_j}$ in the matrix to be inverted in 16 are likely to dominate the entries $\pi_{fp_jp_k}$ and $\pi_{fq_jq_k}$, $k \neq j$. Hence the signs and magnitudes of these own second-order derivatives will play an important role in determining the effect of the subsidy. Secondly, the system in 16, while too opaque to be solved analytically, can be solved numerically if estimated profits and semi-elasticities can be recovered and prices as well as qualities are known. I can do so in my empirical setting below. In principle, this system can also be obtained to measure pass-through of a change in marginal cost. The difference is then that the system of first–order conditions will be differentiated with respect to the change in marginal cost. Finally, the case where several multi-product firms produce products with endogenous quality that are subsidized and products with fixed quality that are not subsidized. Note that a similar system can be obtained to analyze pass-through of a shock to the marginal cost of providing quality.