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Adjustable Product Attributes, Indirect Network Effects, and Subsidy Design: The Case of Electric Vehicles

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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 from 2012-2018, I find that a support scheme increased EV sales by 98% but led to strong range distortions. When designing subsidies, these distortions 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 policymakers should carefully weigh the benefits of increasing EV sales against the distortions this causes.

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 tools 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 three fundamental issues. First, 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. Second, the range of EVs is lower than that of traditional gasoline or diesel cars, making it an important dimension of quality. However, firms can adjust the range relatively easily. Third, understanding how price and range decisions 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 indirect network effects and adjustable product attributes. 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 holds range, and in some cases price, decisions fixed. Second, my framework incorporates indirect network effects and their interaction with endogenous price and range choices. Doing so is challenging as indirect network effects can lead to electric cars acting as complements, making it attractive for firms to lower prices to spur charging station entry. On the other hand, firms can increase charging station entry by providing more range, which raises EV prices. As a result, I can evaluate subsidy schemes as my framework links the price and range effects of subsidies to market outcomes. With my framework, I can 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 important network effects on both the EV demand and the charging station entry side. On the car supply side, indirect network effects lower EV markups by around 17% on average. The presence of indirect network effects also has important implications for subsidy design. Charging station subsidies generate additional EV sales and purchase subsidies spur additional charging station entry. Concentrating subsidy spending on purchase subsidies leads to large EV sales but causes strong range distortions as firms respond by selling cheaper, low-range EVs. Concentrating subsidy spending on charging station subsidies generates fewer EV sales than purchase subsidies but also causes fewer range distortions and delivers a larger charging station network. As a consequence, policymakers face a trade-off between maximizing EV sales, maximizing total and consumer surplus, and CO2 emissions, which are minimized when spending is distributed between purchase and charging station subsidies. These findings suggest that policymakers interested in maximizing EV diffusion need to carefully consider the strategic price and range reactions of firms when designing support schemes.

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 exhibits 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). 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.

The substantial indirect network effects I find on both the EV demand and the charging entry side make own-price elasticities larger in absolute value. Not accounting for indirect network effects would lead to an overestimation of EV markups by 24% on average. 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. EV sales would be 64% higher if producers internalized the effect of changing price and range on other EVs in the market. These higher sales come through a large decrease in price and range. Firms sell cheaper, lower–range EVs on which they earn a markup that is 61% lower on average. Charging station entry increases only slightly on the other hand.

I use the model to perform a rich set of counterfactuals. I analyze a German program for purchase and charging station subsidies. I find that this program led to a 98% increase in EV sales. The program also led to cheaper, lower-range EVs on which firms collect a lower markup. Unlike in the case of uni-dimensional pass-through to price (Bulow and Pfleiderer, 1983; Stern, 1987; Weyl and Fabinger, 2013), the direction of these effects is ambiguous and hence an empirical question. Given the two-sided nature of this market, a logical question to ask is whether it is better to subsidize EV purchases or to subsidize charging station entry (Springel, 2021). I find that removing the charging station subsidy would decrease EV sales by 45% and charging stations by 44%. Removing purchase subsidies would decrease EV sales by 36% and charging stations by 3%. 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. 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 and total surplus are maximized when the whole budget is spent on charging subsidies. A mixed purchase subsidy with a flat- and range-based part coupled with a 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 larger range–based purchase subsidies by selling more expensive EVs with a higher range. An increase in the station subsidy induces only small price and range distortions but still increases EV sales through the indirect network effects. These results have important implications for policymakers. The results 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 from increasing EV sales against the range distortion such a strategy causes.

This paper makes several contributions. 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, 2020; Xing, Leard, and Li, 2021), the role of charging stations and indirect network effects (Li, Tong, Xing, and Zhou, 2017; Li, 2019; Springel, 2021; Fournel, 2021), and other margins such as entry of new EVs (Armitage and Pinter, 2021), usage behavior (Sinyashin, 2021), and portfolio effects (Johansen and Munk-Nielsen, 2020). To the best of my knowledge, this is the first paper to combine price and range responses by firms while also modeling how these responses interact with indirect network effects. Doing so allows me to carefully study strategic responses by firms to subsidies and how indirect network effects influence price and range decisions. Second, I contribute to a wider literature studying environmental policies in car markets by offering a comprehensive evaluation of the economic effects of EV subsidies. By studying strategic supply-side responses to subsidy schemes, I contribute to a 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 a strand that studies and compares the effectiveness of different policy tools (Pavan, 2017; Grigolon, Reynaert, and Verboven, 2018; Durrmeyer and Samano, 2018). Finally, 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 in 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 to the approach of Gaudin (2021) who provides a theoretical framework for predicting the directions of price and quality responses to subsidies, taxes, or marginal cost changes.

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 form 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. A predominance of combustion engine cars using gasoline or diesel as fuel has characterized the German market for new cars over the past decades. 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.

2.1 Industry description

The market for electric vehicles. After having been dormant for more than 100 years, electric vehicle technology came back 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" means 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 the goal to contain 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 depend on characteristics such as the driving range or battery size.[1]. Global government spending on EVs

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

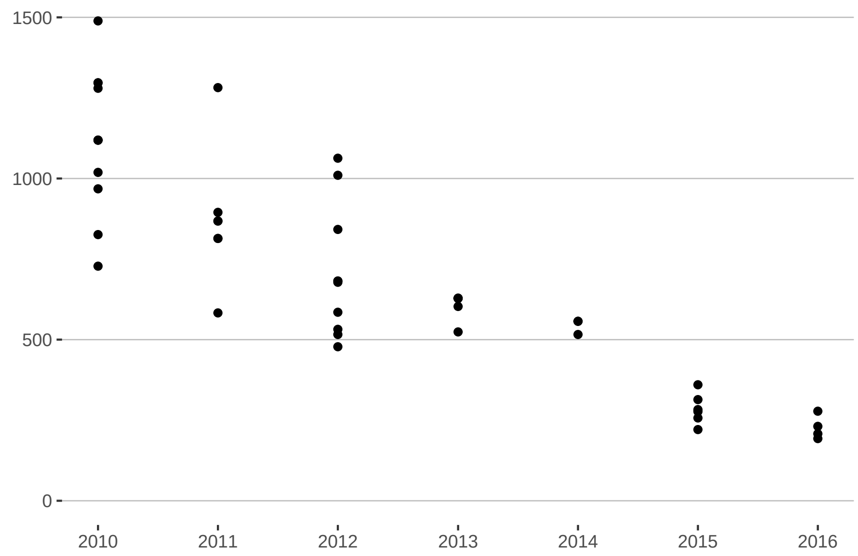

Figure 1: LIC price estimates (USD per kWh)

Source: Hsieh et al. (2019)

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 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, 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 the low range and the low charging station network density contribute to a low perceived quality of EVs and a 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.[2] Germany is home to three of the largest 15 car manufacturers in the world as measured in sales and is ranked fourth in the world in terms of motor vehicle production.

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

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

2016. Part of this program was a support scheme that gave a subsidy of € 2,000 for the purchase of battery electric vehicles and a subsidy of € 1,500 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. In total, the government provided € 600 million in subsidies.[3] The program also provided a total of € 200 million in funding for new charging stations. The amount of the subsidy depended on the type of charging stations. Charging stations with a charging capacity of up to 22 kW are most common and received up to € 3,000 for installation and € 5,000 for connection to the electricity grid (if the charging point was connected to the medium-voltage grid the connection subsidy was up tp € 50,000). The plan reinforced the government's goal to have 1 million electric cars on the streets by 2020 and 6 million by 2030.[4] The budget 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 at 1.2%, with approximately 34,000 annual car sales. These lackluster sales numbers led 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 € 25 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.

2.2 Data

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

Car registrations. I use publicly available data from the German Federal Motor Transport Authority (KBA). This data set contains yearly new registrations at the state level for every car model.[5] 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.

[3] 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`

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

[5] 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).

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).[6] 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).

Demographic 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. 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.

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 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). In aggregating up to this product definition, 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. 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 consist of 28,288 year-state-product observations.

Figure 3 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%. It is unclear from this picture to what extent falling LIC prices and subsidies drove these trends. Detailed summary statistics can be found in Table 8 of Appendix A.

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

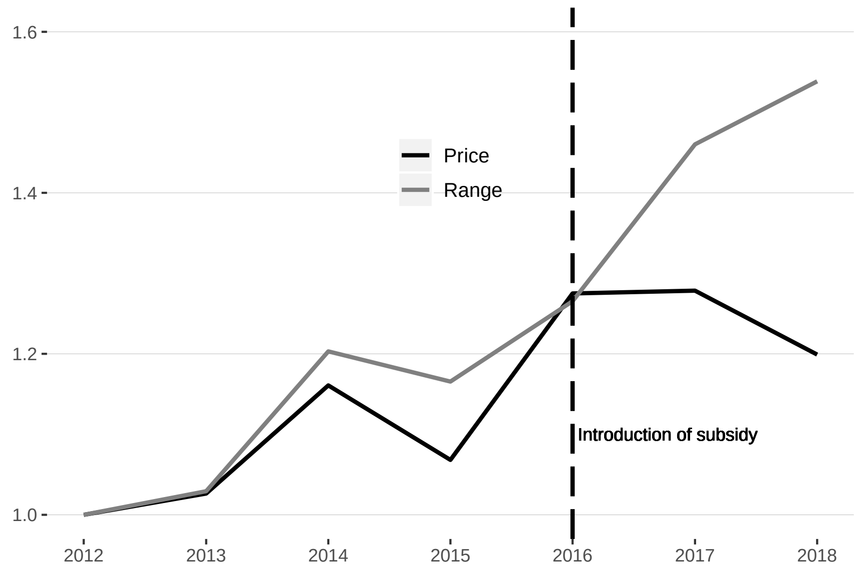

Figure 3: Evolution of price and range of battery electric vehicles (averages, base = 2012)

3 Empirical Model

3.1 Set-up

This section introduces a structural model of demand and supply for new cars and entry of public electric charging stations. The model builds the canonical demand/supply model of Berry et al. (1995) (BLP henceforth) and recent contributions by Fan (2013) and Crawford et al. (2019). The charging entry side builds on Bresnahan and Reiss (1991); Gandal, Kende, and Rob (2000) and Springel (2021). I need a model that generates realistic substitution patterns between electric cars and combustion cars on the demand side where consumer preferences for the number of charging stations generate indirect network effects. On the car supply side, I need to explain how firms choose price and range taking into account the indirect network effects in a multi-product oligopoly. The model also needs to allow me to study the impact of subsidies and marginal cost changes in imperfectly competitive markets when firms choose the price and a product attribute. On the charging station side, I need a framework that links the number of charging stations to the cumulative EV base and the level of subsidies.

Consumers choose the product maximizing their indirect utility and exhibit heterogeneous preferences over prices and product characteristics on the demand side. The supply side allows firms to compete in terms of price and range. 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. Likewise, I assume consumers only care about the electric charging station network and not about the availability of gas stations. These assumptions mirror evidence from consumer surveys on purchase behavior and consumer preferences regarding battery electric vehicles. Several consumer surveys have found that driving range, price, and charging station availability are the most critical consideration in the purchase of an electric vehicle.[7] Additionally, the driving range of combustion engine cars is sufficiently high, and the network of gas stations is sufficiently dense. Hence, these attributes do not play a role in consumer purchase decisions or firms' profit maximization problems.

I further assume that firms choose prices and range simultaneously at the national level. The rationale behind this assumption is that a firm can alter the driving range even after it has fixed other characteristics, such as the car's size dimensions. A battery pack is made up of many lithium-ion cells, giving firms the flexibility to scale the battery pack's size up or down. Additionally, firms choose price and range at the national level because list prices and characteristics do not vary across states. Finally, I assume that firms only choose their battery electric vehicles' range. This assumption is partly a consequence of the fact that I assume consumers do not have preferences on the range of combustion engine cars. In addition, I assume that firms do not choose the range of plug-in hybrid electric vehicles. I do so, first, because the range of PHEVs did not change much over the sample period and, second, because the technology involved is different.[8]

On the charging station side, I assume that charging stations play a complete-information entry game in which they trade off sunk entry costs and future discounted profit streams. These entry costs and profit streams depend on the cumulative EV base and the amount of charging station subsidies, linking both to the amount of charging station entry. One assumption I make on the charging station side is that charging stations are symmetric and end up with identical market shares. Whereas 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.

Timing. I assume that each period starts with a given number of EVs circulating. 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. I will come back to this point at the end of this section. 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. I will return to this point when discussing the counterfactuals.

The model I consider here is static. Using a dynamic specification would make the model richer and enable me to study the chicken-and-egg problem between EV adoption and charging

[7] 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.

[8] The battery of a PHEV needs to work in conjunction with a combustion engine. This setup means that on the one hand, there is less need to increase the range since the combustion engine provides enough range. On the other hand, it is also more difficult to increase the range, given that there are more space constraints.

station entry in more detail. Doing so is infeasible mainly for data reasons, however. 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 demand side since I model substitution between EVs and other cars. Doing so requires taking account of endogenous price and range choices as well as their interaction with indirect network effects and is already challenging. Adding dynamics on top of these challenges is beyond the scope of this paper.

3.2 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

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

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. Remember that consumers only care about the range of electric vehicles. 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. The utility from purchasing the outside option is normalized to $u_{i0mt} = \varepsilon_{i0mt}$.

Consumer i in market mt chooses alternative $j = 0, \dots J$ that maximizes her utility. Each 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. Remember that ε_{ijmt} follows a type-I extreme value distribution. This assumption enables me to derive the probability that product j yields the highest utility across all possible alternatives by integrating over the individual-specific valuations for characteristics:

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

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, and 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.

3.3 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. 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 to both BEVs and PHEVs. I will defer the analysis of the role indirect network effects play in firm decisions to after the introduction of the charging station entry side.

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:

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

where $\mathcal{J}_{ft}$ is the product portfolio of firm f, $mc(\cdot)$ 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 first-order conditions with respect to price and range are then given by

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

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

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 margin 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. We can rewrite (4) as

$$\sum_m \phi_{mt}\Big\{ \underbrace{-\frac{\partial mc_{jt}}{\partial r_{jt}} s_{jmt}}_{\substack{\text{Change in markup x}\\ \text{market share}}} + \underbrace{\big(p_{jt} - mc_{jt}\big)\frac{\partial s_{jmt}}{\partial r_{jt}}}_{\substack{\text{Markup x change}\\ \text{in market share}}} + \underbrace{\sum_{k\neq j, k\in\mathcal{J}_{ft}} \big(p_{kt} - mc_{kt}\big)\frac{\partial s_{kmt}}{\partial r_{jt}}}_{\substack{\text{Cannibalization effect}\\ \text{on other products}}}\Big\} = 0$$

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) as well as the cannibalization effect on the other products in firm f's portfolio. Loosely speaking, equilibrium range decreases with a higher marginal cost of range increases (which squeezes the markup) and increases with larger values of the demand semi-elasticity with respect to range (which increases the extensive margin).

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

$$\begin{cases} \mathbf{s} + (\mathbf{p} - \mathbf{mc})\Delta_p = 0 & (5) \\ -\frac{\partial \mathbf{mc}^B}{\partial \mathbf{r}^B}\mathbf{s} + \Delta_r^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I - \mathbf{mc}^I) = 0, & (6) \end{cases}$$

where $\mathbf{s}$ is the vector of market shares, $\mathbf{p}$ is the vector of prices, $\mathbf{mc}$ is the vector of marginal costs and $\mathbf{r}$ is the vector of range levels.

Marginal cost specification

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

$$\log(mc_{jt}(q_{jt}, w_{jt}; \theta_s)) = \underbrace{w_{jt}\psi + \omega_{jt}}_{\substack{\text{baseline} \\ \text{marginal cost}}} + \underbrace{(\gamma_0 + \gamma_1 t + \eta_{jt})r_{jt}}_{\substack{\text{marginal cost of} \\ \text{providing range}}}, \tag{7}$$

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 (7) 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 costlier at higher range levels.

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

$$\begin{cases} \mathbf{p} = \mathbf{mc} + \Delta_p^{-1}\mathbf{s} & (8) \\ \mathbf{r} = \dfrac{1}{\mathbf{c_1}} \log\left(\dfrac{\Delta_r^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I - \mathbf{mc}^I)}{\mathbf{s}^B\mathbf{c}_1}\right) - \dfrac{\mathbf{c}_0}{\mathbf{c}_1} & (9) \end{cases}$$

We obtain the usual result of the price being equal to marginal cost plus a markup. The expression for range again makes apparent the trade-off in an increase in market share, cannibalization of other products, and a decrease in the margin or vice versa.

Subsidies in the supply model

The supply model above can accommodate subsidies such as that introduced in Germany in 2016. Let p_{jt} be the price paid by consumers and λ_{jt} the subsidy. Then, the price received by firms is $p_{jt} + \lambda_{jt}$. The profit maximization problem of firm f then becomes

$$\max_{p,r} \pi_{ft} \equiv \sum_{j \in J_{ft}} \big(p_{jt} + \lambda_{jt} - mc_{jt}(r_{jt}, w_{jt}; \theta_s)\big) s_{jmt}(p, r, d, x, \xi; \sigma) \mathcal{M}_{mt}, \tag{10}$$

and the system of first-order conditions is now given by

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

where $\boldsymbol{\lambda}$ is the vector of subsidies. Expression (10) also makes apparent that the introduction of a (flat) subsidy is equivalent to a marginal cost decrease of the firm.

3.4 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

$$\mathcal{D}_{hmt}(p_{hmt}, p_{-hmt}, d_{mt})(p_{hmt} - c_{hmt}),$$

where $\mathcal{D}_{hmt}$ is the per-consumer demand for station h, p_{hmt} is the price station h charges and c_{hmt} is the marginal cost of station h. Following Bresnahan and Reiss (1991); Gandal et al. (2000), and Springel (2021), I assume that i) per-consumer demand functions are symmetric, ii) marginal and sunk entry costs are constant across stations and iii) each station h gains an equal share of the market. Under these assumptions, an equilibrium exists in which each station charges the same price and the per-period profits upon entry are

$$\pi_{mt} = Q_{mt}^{EV} \underbrace{\frac{\mathcal{D}(p(d_{mt}))(p - c)}{d_{mt}}}_{\equiv \vartheta(d_{mt})} \tag{13}$$

A station deciding to enter in year t incurs a sunk cost of entry F_{mt} and then earns a sequence of yearly profits

$$-F_{mt} + \rho\pi_{m,t+1} + \rho^2\pi_{m,t+2} + \ldots, \tag{14}$$

with ρ the discount rate. The fact that stations must be indifferent between entering in period t

or in period $t+1$ in a free-entry equilibrium, coupled with equations (13) and (14) then yields

$$\log(\vartheta(d_{mt})) = -\log(\rho) - \log(Q_{mt}^{EV}) + \log\left(F_{mt} - \rho F_{m,t+1}\right) \tag{15}$$

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 charging station subsidies and state fixed effects, I obtain the following estimating equation:

$$log(d_{mt}) = \upsilon_1 + \upsilon_2 \log(Q_{mt}^{EV}) + \upsilon_3 \text{Subsidies}_{mt} + \upsilon_4 \varrho_m + \epsilon_{ct} \tag{16}$$

3.5 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

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

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

$$\gamma_j \equiv \beta^d s_j (1 - s_j).$$

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

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

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

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

We can also express this partial derivative in the following way:

$$\frac{\partial s_j}{\partial p_j} = \eta_{jj} + \underbrace{\eta_{jj}\frac{\upsilon_2\gamma_j}{s^{EV} - \upsilon_2\sum_{k\in\mathcal{J}^{EV}}\gamma_k}}_{\substack{\text{indirect network effects}\\ \text{related to own share}}} + \underbrace{\sum_{k\neq j}\eta_{kj}\frac{\upsilon_2\gamma_j}{s^{EV} - \upsilon_2\sum_{k\in\mathcal{J}^{EV}}\gamma_k}}_{\substack{\text{indirect network effects}\\ \text{related to rival shares}}} \tag{17}$$

Assuming that $s^{EV} - \upsilon_2\sum_k\gamma_k > 0$ [9] 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

$$\begin{aligned}\frac{s_j}{p_k} &= \eta_{jk} + \frac{\upsilon_2}{s^{EV}}\gamma_j\frac{\partial s}{\partial p_k}\\ &= \eta_{jk} + \upsilon_2\gamma_j\frac{\sum_{l\in\mathcal{J}^{EV}}\eta_{lk}}{s^{EV} - \upsilon_2\sum_{l\in\mathcal{J}^{EV}}\gamma_l}\end{aligned} \tag{18}$$

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 be a mirror case of the analysis on price derivatives above: 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.

4 Estimation

4.1 Instrumental variables

Car demand. Estimation of the demand side parameters suffers from the well-known endogeneity issue related to price and here also to range: As the demand- and supply-side shocks realize before the price and range choices, price and range may be correlated with these un-

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

observables. 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, 2019). 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 for 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, a *quadratic* variant that sums squared differences between product characteristics, and a *discrete* variant for discrete variables that counts the number of products with the same value for the characteristic:

$$
\begin{aligned}
Z_{jt}^{k,\text{local}} &= \sum_{r \in \mathcal{C} \setminus \{j\}} \mathbf{1}\{|d_{jrt}^{k}| < sd(d^{k})\} \\
Z_{jt}^{k,\text{quadratic}} &= \sum_{r \in \mathcal{C} \setminus \{j\}} d_{jrt}^{k2} \\
Z_{jt}^{k,\text{discrete}} &= \sum_{r \in \mathcal{C} \setminus \{j\}} \mathbf{1}\{|d_{jrt}^{k}| = 0\}
\end{aligned}
$$

where $|d_{jrt}^{k}|$ is the absolute value of the difference between products j and r in characteristic k, $sd(d^{k})$ is the standard deviation of characteristic k across markets, and $\mathcal{C}$ is the set of products considered. 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. 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.

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.

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.

4.3 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 accommodating zero sales in random coefficient demand models.[10] I follow D'Haultfœuille, Durrmeyer, and Février (2019) and use a simple correction of market shares:

$$s_j^c = \frac{q_j^{obs} + 0.5}{\mathcal{M}},$$

where q_j^{obs} is the observed quantity sold of product j in a given market and $\mathcal{M}$ is the market size in that market. This correction aims to minimize the bias of $\log(s_j)$ 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 $q_j = 0$ with $q_j = 1$, see Appendix C), which I see as evidence that my demand parameters are consistently estimated and lead me to believe that the correction I use is sufficient.

4.4 Estimation of the car demand side

On the demand side, the vector of parameters to be estimated is given by $\theta_d \equiv (\beta_i^x, \beta^r, \alpha)$. I allow random coefficients on characteristics for which I believe consumer heterogeneity matters: an *EV* dummy for battery- and plug-in hybrid vehicles and *Fuel Cost*, measured in €/100 km. The random coefficient on the *EV* dummy allows 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 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 allow 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 dummy if the firm has its headquarters in the state considered, and a linear time trend.[11] I 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 $E[z_{jmt}^d \xi_{jmt}] = 0$, with z_{jmt}^d as an instrument. Stacking

[10]Li (2019) uses a Bayesian shrinkage estimator to move market shares away from zero. Lu, Shi, and Gandhi (2020) 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.

[11]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.

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.

4.5 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 (5) and (6) can be solved for the pair of supply-side unobservable vectors $\boldsymbol{\omega}$ and $\boldsymbol{\eta}$. 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 $\rho_{jt} = (\omega_{jt}, \eta_{jt})$ 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 (11)-(12). 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.[12] 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.

4.6 Estimation of the charging station entry side

Estimation of the charging station side is straightforward. Once I obtain (16), I estimate v using two-stage least squares. In the estimation, I include national-level subsidies, state-level subsidies, and a "Support" variable. The "Support" is equal to one if a state offers special incentives for charging stations not easily measurable in monetary terms, such as interest-free loans. This variable is also equal to one if a state grants subsidies that I cannot measure in per-station terms (such as a state offering 30% of installation costs). I set the national-level subsidies equal to € 8,000. The vast majority of stations (around 87.5%) 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.

5 Results

The estimated coefficients of key parameters are in Table 1. The first three columns show demand estimates, and the last three columns show marginal cost estimates along with standard errors in parentheses. Table 9 in Appendix A reports first-stage regressions. Table 10 in Appendix B reports the results when assuming firms and charging stations move simultaneously. Overall, the signs and magnitudes of the estimated coefficients are in line with standard economic intuition.

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

Table 1: Key estimates

Demand/supply for cars			Station entry		
	Coefficient	SE		Coefficient	SE
Demand: Means					
Range	2.364	(0.313)	log(EV base)	0.715	(0.129)
Range x Trend	-0.252	(0.037)	Subsidies	0.105	(0.036)
log(Charging Stations)	0.768	(0.106)			
Fuel Cost	-0.322	(0.040)			
BEV	-13.933	(4.330)			
PHEV	-11.499	(4.050)			
Demand: Interactions					
Price / Income	-6.338	(0.628)			
Demand: St. Dev.					
EV	-3.603	(1.559)			
Fuel Cost	-0.154	(0.024)			
Supply: Range provision					
Intercept	0.842	(0.022)			
Trend	-0.096	(0.005)			
Statistics					
Mean own-price elasticity	-3.544				
Mean own-range elasticity (BEVs)	3.194				
Mean markup (BEVs) (€ 1,000)	7.885				

Note: Prices, subsidies deflated and in EUR 1,000. Vehicle class-, Body-, Firm- and State Fixed Effects included on car demand- and supply side.

Consumers like greater range, all else equal. The range-specific trend is negative, meaning that consumer preferences for range become less intense throughout the sample period. One explanation for this could be that range anxiety has decreased over time due to consumers learning more about electric vehicles. This learning may come from their own experience, that of peers, or simply 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. Such an increase in the range of electric vehicles has indeed occurred, as evidenced in Figure 3. 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, 2019; Springel, 2021). The mean range elasticity is equal to 3.223.

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 -3.554, which falls within the range of figures found in the long literature on demand estimation for new car markets. Table 13 in Appendix D shows how my estimated price elasticity compares to those found in other papers. Unlike the sensitivity of range, price sensitivity barely changes over the sample period. Due to slightly larger and slightly 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.

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.

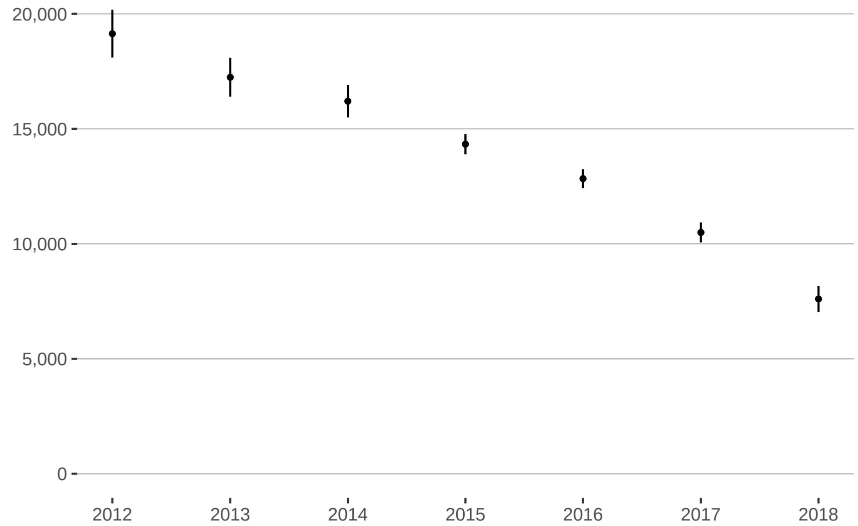

Figure 4: Estimated yearly mean marginal cost of providing range

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 64% from 2012 to 2018 (see Figure 4). This number is comparable to the estimates of lithium-ion cell price decreases in Hsieh et al. (2019), for instance.

Figure 6 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 and the mean

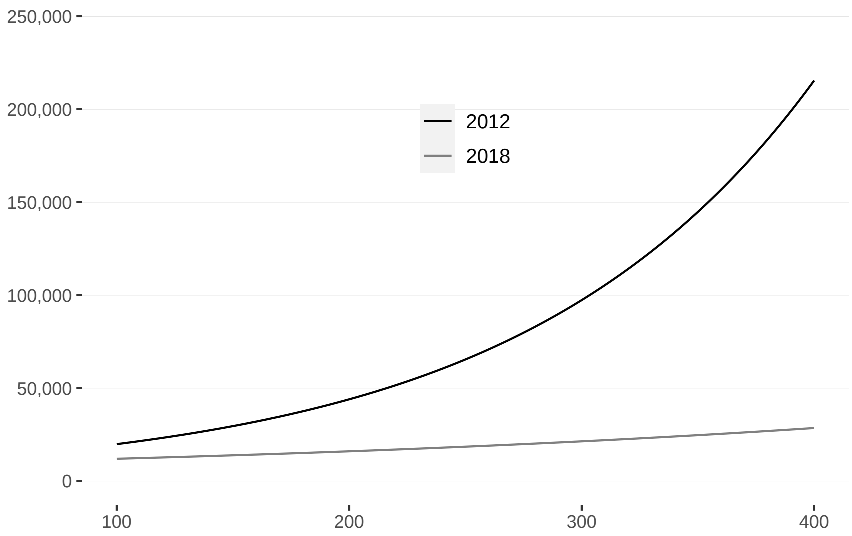

Figure 6: Estimated marginal cost functions for 2012 and 2018

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 200 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.

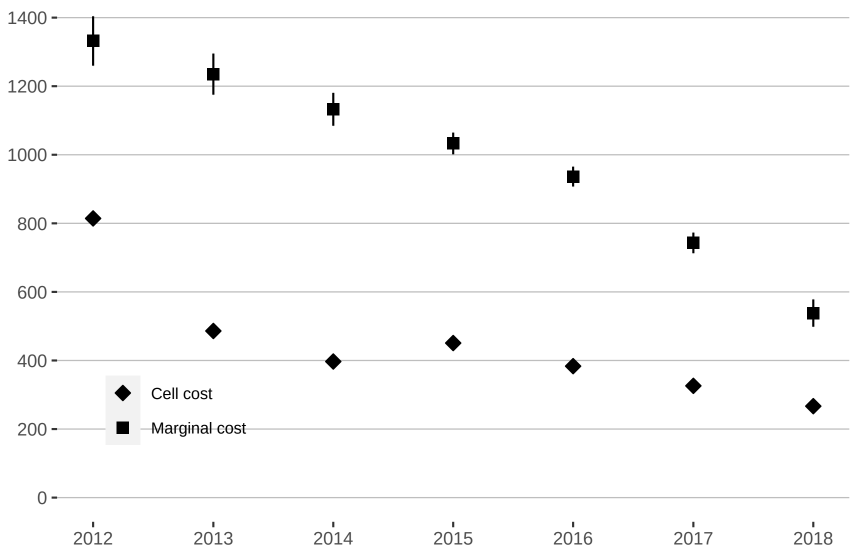

Figure 7: Per-kWh cost at observed range levels against battery pack cost

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, Lebedeva, Di Persio, and Boon-Brett, 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 7. 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 2012, 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 62% 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 1 suggests the presence of strong indirect network effects on both the EV demand- and the charging station entry side. We saw in Section 3.5 that indirect network effects alter the market share derivatives with respect to price and range and hence the price and range elasticities. Through affecting pricing decisions, indirect network effects also affect markups. Shutting down indirect network effects in firm decisions would lead to an over-estimation of markups of around 24% on average. Table 2 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 €1,600 lower when taking into account indirect network effects. Note that indirect network effects also accrue to PHEVs, whose markups are over-estimated by 16.7% when failing to take account of indirect network effects.

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

	i3	Soul	i.MiEV	Leaf	Golf	up.
With indirect network effects						
i3	1.7976	0.0949	0.0988	0.0942	0.0929	0.0988
Soul	0.0633	2.1950	0.0660	0.0642	0.0632	0.0659
i.MiEV	0.0005	0.0005	1.2812	0.0005	0.0005	0.0005
Leaf	0.0775	0.0794	0.0810	2.5120	0.0778	0.0808
Golf	0.1413	0.1451	0.1494	0.1446	2.1146	0.1491
up.	0.0167	0.0167	0.0168	0.0167	0.0165	1.1607
Without indirect network effects						
i3	1.6758	-0.0295	-0.0263	-0.0297	-0.0298	-0.0259
Soul	-0.0201	2.1149	-0.0183	-0.0196	-0.0196	-0.0181
i.MiEV	-0.0001	-0.0001	1.2806	-0.0001	-0.0001	-0.0001
Leaf	-0.0218	-0.0213	-0.0202	2.4119	-0.0213	-0.0200
Golf	-0.0407	-0.0387	-0.0357	-0.0389	1.9333	-0.0354
up.	-0.0034	-0.0036	-0.0037	-0.0036	-0.0036	1.1404

Table 2: Mean own-and cross-price elasticities of selected BEVs in 2018

	i3	Soul	i.MiEV	Leaf	Golf	up.	Markup
With indirect network effects							
i3	-4.0878	-0.2291	-0.2321	-0.2278	-0.2248	-0.2315	8,152
Soul	-0.1165	-3.7431	-0.1149	-0.1156	-0.1139	-0.1144	7,229
i.MiEV	-0.0015	-0.0015	-3.2026	-0.0015	-0.0015	-0.0015	6,133
Leaf	-0.1283	-0.1284	-0.1276	-3.7892	-0.1262	-0.1270	7,483
Golf	-0.2883	-0.2879	-0.2867	-0.2875	-3.9293	-0.2853	7,820
up.	-0.0499	-0.0492	-0.0481	-0.0492	-0.0485	-3.1849	5,623
Without indirect network effects							
i3	-3.7991	0.0658	0.0644	0.0658	0.0659	0.0641	10,776
Soul	0.0296	-3.6027	0.0328	0.0312	0.0312	0.0328	9,468
i.MiEV	0.0002	0.0003	-3.2008	0.0003	0.0003	0.0003	7,841
Leaf	0.0299	0.0318	0.0335	-3.6298	0.0316	0.0336	9,121
Golf	0.0632	0.0672	0.0709	0.0669	-3.5791	0.0711	9,883
up.	0.0077	0.0089	0.0104	0.0088	0.0087	-3.1266	8,144

We can see similar patterns in Table 3 that 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.

6 Counterfactuals

In this section, I use the estimated model to quantify the effect of marginal cost changes and subsidies on battery electric vehicles by performing several counterfactual exercises. In a first step, I analyze the impact of indirect network effects on price and range choices as well as market outcomes. 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.

6.1 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 (11). 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 (12). 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 (15) 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, 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 $r_{max,j} \equiv \big(\log(mc_j) - c_{0j}\big)/c_{1min}$. 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.

6.2 How do indirect network effects affect price and range decisions?

I find that ignoring indirect network effects leads to an over-estimation of markups by around 24% 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 4. 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 additional sales and strong charging station entry. Overall, consumer surplus would increase by around €254 million in this case. 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 may be that range and charging stations are substitutes from a consumer

Table 4: Market outcomes with different market structures

	Data	No internalization	Full internalization
Price	34,671	+2,767 (+63, +4,944)	-8,310 (-10,906, -785)
Range	259	+21 (+1, +38)	-61 (-88, -16)
MC	28,483	+1,492 (-307, +3,285)	-4,148 (-5,265, +234)
Markup	8,077	-614 (-2,377, +693)	-6,051 (-8,019, -2,971)
Sales	34,761	-4,723 (-10,333, +8,370)	+20,651 (+2,924, +51,280)
Stations	17,511	-539 (-4,409, +13,382)	+1,883 (-3,275, +18,585)
Consumer surplus	48,566	-78 (-2,340, +2,866)	+254 (-1,817, +3,195)
CO2 emissions	5,192,205	-38 (-6,605, +3,139)	-1,119 (-13,365, +1,547)

Note: Table gives differences to observed outcomes with 90% C.I. in parentheses.

point of view. Then, an increase in charging stations may make it possible for firms to reduce range and generate additional sales by further reducing the price.

6.3 What was the impact of the German subsidy scheme?

In the next step, 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 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 the introduction of this support scheme. To do so, I re-compute 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. In all scenarios, I leave the subsidies for PHEVs unchanged. Likewise, I leave any state-level subsidies in place. Table 5 shows the outcomes for these three scenarios. Column 3 shows outcomes when the whole scheme is removed and columns 4 and 5 show outcomes when only the purchase subsidy and only the station subsidy are removed, respectively.

Removing the whole support scheme would have resulted in more expensive BEVs with a higher range. Firms would have collected a larger markup on these BEVs. When comparing the first four rows across columns 3-5, we see that the strategic price and range reactions are mainly due to the purchase subsidy. Note that this purchase subsidy is equivalent to a reduction in the marginal cost from the point of view of firms. In Appendix E I show that the direction of firms' price and range reactions is unclear a priori.[13] Figure 8 shows that the direction of price

[13] Gaudin (2021) shows that the direction of such strategic reactions are ambiguous even in simpler models

and range effects goes into the same reaction 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. When only the charging station subsidy is removed, strategic price and range reactions are small.

Table 5: Market outcomes without subsidy

	With subsidy	Neither subsidy	No BEV subsidy	No station subsidy
Price	34,671	+6,374 (+4,218, +7,701)	+6,034 (+4,053, +7,236)	+817 (-513, +1,700)
Range	259	+44 (+24, +76)	+40 (+21, +69)	+8 (-2, +19)
MC	28,483	+3,443 (+1,827, +4,378)	+3,119 (+1,569, +4,069)	+684 (-390, +1,352)
Markup	8,077	+1,042 (+529, +1,353)	+1,026 (+565, +1,306)	+133 (-165, +348)
Sales	34,761	-17,069 (-18,954, -12,414)	-9,004 (-13,358, +743)	-11,149 (-13,966, -6,275)
Stations	17,511	-7,946 (-7,951, -4,903)	-891 (-4,676, +12,498)	-7,939 (-7,951, -4,381)
Government spending	130.62	-131	-74 (-104, +33)	-85 (-91, -76)
Consumer Surplus	48,566	-374 (-2,648, +2,463)	-125 (-2,357, +2,843)	-306 (-2,582, +2,534)
CO2 emissions	5,192,205	+5,682 (+1,785, +11,682)	+2,015 (-3,070, +5,176)	+4,413 (+1,223, +8,983)

Note: Table gives differences to observed outcomes with 90% C.I. in parentheses.

When looking at rows 5-8, we see first that EV sales almost and station entry more than doubled due to the support scheme. Consumer surplus increased by around € 374 million whereas the scheme cost € 131 million. The role of indirect network effects also becomes obvious: Removing the purchase subsidy leads to lower charging station entry. Likewise, removing the charging station subsidy leads to lower BEV sales. In fact, the charging station subsidy seems to have generated more BEV sales than the direct purchase subsidy. Removing it would also lower consumer surplus by more than twice the amount when removing the purchase subsidy. One reason for this result is that the charging station subsidy generates strong feedback loops without causing large distortions in BEV price and range levels.

From this exercise, it seems like station subsidies generate larger gains in EV sales and consumer surplus than purchase subsidies. However, the exercise above did 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 them holding expenditure levels constant, which is what I do in the next step.

assuming symmetry and single-product firms.

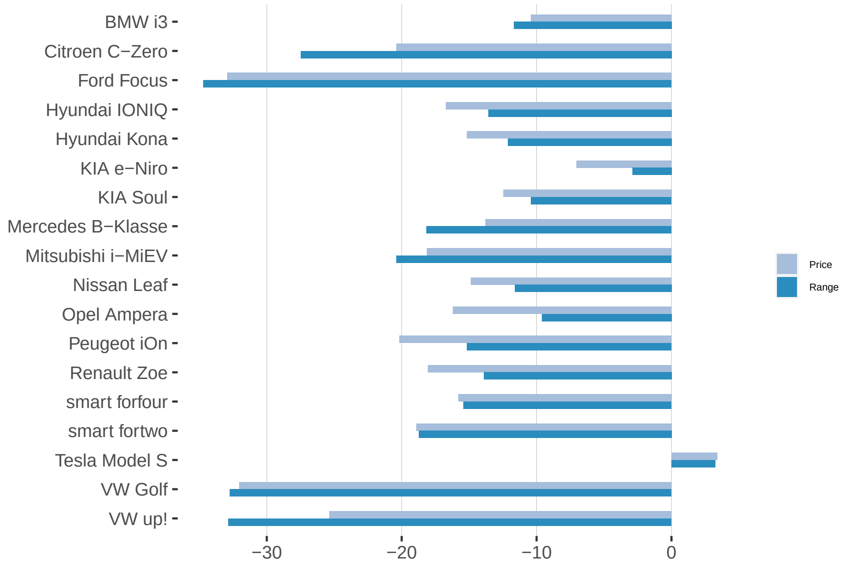

Figure 8: Percentage changes of price and range due to introduction of subsidy

6.4 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. Moreover, I allow purchase subsidies to depend on the range. The reasons for doing so are twofold. First, policymakers in some countries use attribute-based subsidies. For instance, the total subsidy in California and China is or was a function of the driving range or the size of the battery pack (Rokadiya and Yang, 2019). Second, doing so gives the policymaker the choice between subsidizing two attributes that enhance BEV quality, creating an interesting choice: On the one hand, the policymaker can directly incentivize range provision and steer consumers towards higher-range cars. On the other hand, she can incentivize charging station entry which will benefit all BEVs and their buyers equally.

In particular, 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 $\lambda_j = \lambda_1 + \lambda_2 r_j$. Note that while simple, this scheme nests both the case of a flat subsidy and a purely range-based subsidy. When λ_2 is zero, we recover a simple flat subsidy of the form implemented in Germany. When λ_1 is zero, the subsidy depends purely on the range. In that case, the subsidy is equivalent to a decrease in the marginal cost of providing range. On the other hand, a flat subsidy is equivalent to a general marginal cost decrease. In other words, a flat subsidy lets firms choose how to "interpret" the marginal cost decrease: They can treat it as making range provision cheaper or as reducing the total marginal cost of producing the product. By contrast, a pure range-based subsidy forces firms to treat the subsidy as a decrease in the marginal cost of providing range. One can interpret the intermediate cases where both λ_1 and λ_2 are non-zero as putting weights on a general and a range-specific marginal cost decrease.

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 6.1 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[14], 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 the German Federal Highway Research Institute (Bäumer, Hautzinger, Pfeiffer, Stock, Lenz, Kuhnimhof, and Köhler, 2017).[15]

Note that in the computation of fleet emissions, I assume that BEVs' CO2 emissions are equal to zero. Of course, 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.

I focus on three outcomes in this section: First, I look at CO2 emissions from new car sales. Focusing on this target makes sense, as the ultimate goal of subsidizing BEVs is to decarbonize the transport sector. The fewer vehicles emitting CO2 sold, the lower are the CO2 emissions from the existing vehicle stock. Second, I focus on diffusion. This target makes sense for two reasons. First, many governments have introduced explicit sales targets for electric vehicles. A diffusion-maximizing approach ensures the achievement of these sales targets. Second, a strategy focusing on maximizing diffusion can also be a static approximation to a dynamic optimization problem: A policymaker quickly wants to move down a learning curve. A diffusion-maximizing strategy can approximate well the desire to move down the learning curve swiftly in the early phase of adoption. An interpretation of sales targets can be that the policymaker simplifies the complicated dynamic optimization problem by defining short- and medium-run sales targets that allow the industry to move down the learning curve quickly. Third, I look at consumer surplus, as well as total surplus. When calculating total surplus I take

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

[15]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 6: Comparison of subsidy schemes

Scheme $(\lambda_1, \lambda_2, \lambda_3)$, in K€	Price in €	Range in km	Sales	Stations	CO2 in t	CS in M€	TS in M€
(0, 0, 0)	41,078	303	17,429	9,567	5,198,447	48,224	77,281
(2, 0, 8)	-6,408	-44	+17,332	+7,944	-6,242	+342	+472
(0, 0, 10.28)	-687	-7	+12,839	+12,714	-5,148	+429	+582
(1, 0.55, 7.4)	-2,612	+4	+15,151	+6,653	-6,481	+330	+450
(2.7, 0, 6.75)	-8,229	-56	+17,995	+5,696	-6,134	+286	+400

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 ($\boldsymbol{\lambda} = (2, 0, 8)$).[16] We can see that different schemes maximize different policy objectives. By increasing the (flat) purchase subsidy and decreasing the charging station subsidy, the policymaker can maximize BEV sales. By decreasing the flat part of the purchase subsidy and the charging station subsidy to introduce a range-based purchase subsidy, she can minimize CO2 emissions from new car sales. By purely subsidizing charging stations, the policymaker can maximize consumer surplus as well as total surplus.[17] We can also see that schemes that employ purchase subsidies lead to strong price and range reactions by firms. Consumers seem to have strong preferences for both higher range and a large charging station network. On the other hand, a high flat purchase subsidy incentivizes firms to sell cheaper, lower-range BEVs. Consequently, consumer surplus (as well as total surplus) maximization requires a scheme causing small price and range reactions by firms and a large amount of charging station entry, which happens when only subsidizing the charging station side. In that case, fewer consumers buy a BEV, but the BEVs sold have a high range and profit from a large charging station network. Note that the environmental benefits from purely subsidizing charging stations may be understated to the extent that more 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).

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 around 75% of the substitution towards EVs comes from the outside option, meaning that the new car market overall expands. Substitution from the outside option can come from consumers who otherwise would have bought a used car or consumers who would not have bought a car at all. To the extent that the subsidy generates substitution from the used car market, the environmental benefits of the subsidy scheme are higher than reported as used cars in 2018 were predominantly combustion cars. Substitution from con-

[16] Table 11 in Appendix B reports the results when assuming firms and charging stations move simultaneously.

[17] Note that only subsidizing charging stations also maximizes total surplus when considering a higher or lower social cost of carbon emissions (such as €200 or €25).

Table 7: Substitution patterns across subsidy schemes

Scheme	Substitution from:		Substitution to	
	ICE	Outside option	BEV	PHEV
(0, 0, 0)	0	0	0	0
(2, 0, 12)	5,813	18,911	17,332	7,392
(0, 0, 10.28)	6,917	18,670	12,839	12,748
(1, 0.55, 7.4)	5,496	16,025	15,151	6,370
(2.7, 0, 6.75)	4,991	17,977	17,995	4,972

sumers who would not have bought a car at all lowers the effectiveness of the subsidy scheme as its main stated goal is to electrify private transport and not expand car ownership.[18] This table also explains why the scheme $\boldsymbol{\lambda} = (1, 0.55, 7.4)$ 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 hand. While the scheme that only subsidizes charging stations generates both the largest amount of substitution from combustion cars and also generates substitution from more polluting cars, almost half of the substitution goes towards PHEVs that are not zero-emission. The large amount of substitution towards PHEVs is the reason why this scheme does 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, at the observed scheme, BEVs are cheaper and have a lower range, generating substitution mainly from smaller, less polluting combustion cars.

In this section, we have seen that a policymaker faces a trade-off between maximizing BEV sales, minimizing CO2 emissions from new car sales, and maximizing consumer and total surplus. The main drivers behind this finding are strategic price and range reactions to subsidies by firms that interact with indirect network effects. Firms react to flat purchase subsidies by decreasing both the price and range of BEVs that generate large sales and important indirect network effects and to range-based subsidies by lowering the price and increasing the range of BEVs that generate fewer sales and indirect network effects but lead to lower CO2 emissions from new car sales. Since consumers have strong preferences for both range and charging stations, they prefer a scheme that delivers both high-range BEVs and a large station network. To achieve this outcome, the policymaker needs to minimize price and range reactions by shutting down the purchase subsidy. Note that the policymaker can always achieve a combination of higher BEV sales, lower CO2 emissions from new car sales, and higher consumer and total surplus. In fact, the observed scheme, while not optimizing any policy goals, actually delivers the second-highest EV sales, consumer and total surplus, and the second-lowest CO2 emis-

[18] In addition, more cars overall create further negative externalities, such as local pollution from breaking and accelerating and road congestion.

sions.

7 Conclusion

In this paper, I study subsidy design in the presence of indirect network effects and adjustable product attributes. In particular, I analyze how indirect network effects affect price and product attribute decisions of firms 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 networks effects into account. Not accounting for these effects would also lead to an overestimation of EV markups by 24% 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 60% from 2012 to 2018.

I analyze a German program for purchase and charging station subsidies. I find that this program led to a 98% increase in EV sales. The program also led to cheaper, lower-range EVs on which firms collect a lower markup. Compared to the scenario in which firms fully internalize effects on rival EVs, price, range, and markups are higher and the charging station network substantially larger under the subsidy. I find that removing the charging station subsidy would decrease EV sales by 45% and charging stations by 44%. Removing purchase subsidies would decrease EV sales by 36% and charging stations by 3%.

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, 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 whole budget being spent on charging subsidies. A mixed purchase subsidy with a flat- and range-based part coupled with a charging subsidy minimizes CO2 emissions from new car sales. The subsidy maximizing total surplus coincides with the scheme maximizing consumer surplus.

The results have implications for policymakers. It is crucial to understand substitution patterns and strategic firm reactions generated by different subsidy schemes, as they shape the effects of subsidies. Consumers prefer subsidy schemes that lead to only small strategic reactions by firms and deliver high-range BEVs and a large charging station network.

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 absent coordination or some other kind of intervention.

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Appendix

For Online Publication

A Additional Figures and Tables

Table 8: Summary statistics

Mean values of key characteristics

Variable	2012	2013	2014	2015	2016	2017	2018
BEV							
Price	30,490	31,295	35,392	32,569	37,104	37,200	34,671
Range (in km)	168	173	202	196	213	246	259
Fuel Cost	4.02	4.34	4.37	4.19	4.24	4.28	4.21
Acceleration	2.8	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	6.4	6.78	6.78	7.03	7.13	6.97
Doors	4.5	4.7	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	43,288	48,472	44,265	56,007	57,479	54,651	57,126
Range (in km)	54	53	52	44	40	45	45
Fuel Cost	5.29	5.64	5.76	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	32,582	32,873	33,914	33,881	34,653	33,669	33,652
Range (in km)	995	1,018	1,039	1,057	1,063	1,023	997
Fuel Cost	10.06	9.32	8.62	7.6	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	8.04	8.07	8.08	8.1	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	1,116	1,466	2,243	3,530	6,053	9,803	16,307

Table 9: First Stage Estimates

.	Price		Range		Range x Trend		Stations	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Exogenous Charac.								
Fuel Cost	-0.910	(0.029)	0.003	(0.001)	0.001	(0.003)	0.002	(0.001)
Footprint	9.472	(0.089)	0.049	(0.002)	0.204	(0.010)	0.000	(0.001)
Acceleration	3.599	(0.046)	-0.014	(0.001)	-0.060	(0.005)	0.000	(0.001)
Doors	0.091	(0.062)	-0.020	(0.001)	-0.095	(0.006)	0.001	(0.001)
BEV	22.961	(3.036)	1.525	(0.160)	-1.446	(0.774)	-0.430	(0.213)
PHEV	21.685	(2.716)	0.185	(0.158)	6.075	(0.729)	-0.352	(0.198)
Own State	2.324	(0.346)	0.009	(0.012)	-0.005	(0.061)	0.093	(0.014)
Trend	-0.293	(0.034)	0.004	(0.002)	0.086	(0.008)	-0.006	(0.002)
PHEV								
Range x PHEV	-7.376	(0.897)	1.369	(0.049)	4.061	(0.254)	-0.157	(0.102)
Cost shifters								
Station Subsidies	0.022	(0.036)	0.006	(0.003)	0.156	(0.014)	0.101	(0.005)
Differentiation IVs								
BEV count-local-rival	0.270	(0.106)	0.089	(0.006)	1.280	(0.042)	0.003	(0.006)
EV efficiency-local-own	-2.681	(0.115)	-0.131	(0.012)	-0.621	(0.071)	0.012	(0.012)
EV efficiency-local-rival	0.054	(0.013)	0.001	(0.001)	0.029	(0.003)	-0.002	(0.001)
EV efficiency-local-own-nest	2.464	(0.111)	0.137	(0.012)	0.666	(0.071)	-0.015	(0.012)
Footprint-local-own	21.849	(1.188)	1.073	(0.050)	5.017	(0.280)	0.047	(0.043)
Footprint-local-rival	-0.697	(0.363)	-0.049	(0.006)	-0.221	(0.026)	-0.006	(0.005)
Price-local-own	-11.969	(1.436)	-1.323	(0.097)	-5.372	(0.459)	-0.007	(0.067)
Price-quadratic-own	0.235	(0.009)	-0.005	(0.000)	-0.020	(0.002)	0.000	(0.000)
Weight-local-rival	-11.758	(0.346)	0.020	(0.003)	0.061	(0.011)	0.002	(0.003)
Fuel efficiency-quadratic-rival	0.321	(0.108)	-0.005	(0.001)	-0.008	(0.004)	-0.002	(0.001)
Firm FE	X		X		X		X	
Class FE	X		X		X		X	
Body FE	X		X		X		X	
State FE	X		X		X		X	
SW F-Stat	319.954		368.319		223.939		128.393	
Observations	28288		28288		28288		28288	

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

B 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 10 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 11 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 11 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 6.4. 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 6.4 go through.

Table 10: Estimation results

Demand/supply for cars			Station entry		
	Coefficient	SE		Coefficient	SE
Demand: Means					
Range	2.364	(0.313)	log(EV base)	0.715	(0.129)
Range x Trend	-0.252	(0.037)	Subsidies	0.105	(0.036)
log(Charging Stations)	0.768	(0.106)			
Fuel Cost	-0.322	(0.04)			
BEV	-13.933	(4.33)			
PHEV	-11.499	(4.05)			
Demand: Interactions					
Price / Income	-6.338	(0.628)			
Demand: St. Dev.					
EV	-3.603	(1.559)			
Fuel Cost	-0.154	(0.024)			
Supply: Range provision					
Intercept	0.929	(0.024)			
Trend	-0.109	(0.005)			
Statistics					
Mean own-price elasticity	-3.544				
Mean own-range elasticity (BEVs)	3.028				
Mean markup (BEVs) (€ 1,000)	9.510				

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

Table 11: Comparison of subsidy schemes (simultaneous moves)

Scheme	Price	Range	Sales	Stations	CO2	CS	TS
(0, 0, 0)	40,793	298	17,282	9,567	5,197,762	48,207	77332
(2, 0, 8)	-6,122	-39	+17,479	+7,944	-5,558	+359	+538
(0, 0, 10.285)	-685	-6	+ 12,981	+12,686	-4,183	438	+643
(1.5, 0.5, 6.85)	-3,569	-2	+15,828	+5,712	-5,757	+317	+476
(2.85, 0, 6.4)	-8,250	-53	+18,174	+5,131	-5,596	+289	+440

C Robustness to alternative corrections

Table 12 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 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 12: Estimates of key parameters under alternative corrections for zero market shares

	Min bias	**Laplace**	**Naive**
Mean Utility			
Range	2.364	2.206	2.337
	(0.313)	(0.287)	(0.305)
Range x Trend	-0.252	-0.231	-0.245
	(0.037)	(0.033)	(0.036)
Charging Stations	0.768	0.684	0.746
	(0.106)	(0.107)	(0.106)
Fuel Cost	-0.322	-0.318	-0.326
	(0.040)	(0.038)	(0.039)
BEV	-13.933	-12.167	-13.481
	(4.330)	(4.257)	(4.235)
PHEV	-11.499	-9.949	-11.124
	(4.050)	(3.985)	(3.952)
Interactions			
Price / Income	-6.338	-5.896	-6.392
	(0.628)	(0.586)	(0.618)
Standard Dev.			
EV	3.603	3.129	3.479
	(1.559)	(1.598)	(1.534)
Fuel Cost	0.154	0.153	0.155
	(0.024)	(0.022)	(0.023)

Note: Standard errors in parentheses.

D Estimated price elasticities in selected papers

Table 13 presents estimates of price elasticities from several papers using a similar structural model of demand to mine.

Table 13: 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 (2019)	-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

Own estimated price elasticity: -3.544
[1] Conlon and Gortmaker (2020) replication
[2] Conlon and Gortmaker (2020) own procedure
[3] Range of elasticities for EVs

E A model of quality provision

E.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.[19] 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 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

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

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

$$c_q = \frac{\partial s(p, q)/\partial q}{|\partial s(p, q)/\partial p|}, \tag{19}$$

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 (19), 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

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

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

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

We can then conclude that

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

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.

E.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 $j = 1, \ldots J$ 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 $j \in \mathcal{I}$.[20] 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 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 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

[20] 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.

$J + J_q$ equations:

$$[p_1]: \quad \pi_{f(1)p_1} \equiv s_1 + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial p_1} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial p_1} = 0$$

$$\vdots$$

$$[p_J]: \quad \pi_{f(J)p_J} \equiv s_J + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial p_J} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial p_J} = 0$$

$$[q_1]: \quad \pi_{f(1)q_1} \equiv -c_{q_1} s_1 + \sum_{k \in \mathcal{J}_{f(1)} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial q_1} + \sum_{l \in \mathcal{J}_{f(1)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial q_1} = 0$$

$$\vdots$$

$$[q_{J_\mathcal{B}}]: \quad \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}} \equiv -c_{q_{J_\mathcal{B}}} s_{J_\mathcal{B}} + \sum_{k \in \mathcal{J}_{f(J_\mathcal{B})} \cap k \in \mathcal{B}} (p_k + \lambda - c_k) \frac{\partial s_k}{\partial q_{J_\mathcal{B}}} + \sum_{l \in \mathcal{J}_{f(J)} \cap l \in \mathcal{I}} (p_l - c_l) \frac{\partial s_l}{\partial q_{J_\mathcal{B}}} = 0$$

The total differentiation of this system yields

$$\begin{bmatrix} \frac{dp_1}{d\lambda} \\ \vdots \\ \frac{dp_J}{d\lambda} \\ \frac{dq_1}{d\lambda} \\ \vdots \\ \frac{dq_{J_\mathcal{B}}}{d\lambda} \end{bmatrix} = \begin{bmatrix} \pi_{f(1)p_1p_1} & \cdots & \pi_{f(J)p_Jp_1} & \pi_{f(1)q_1p_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1p_J} & \cdots & \pi_{f(J)p_Jp_J} & \pi_{f(1)q_1p_J} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_J} \\ \pi_{f(1)p_1q_1} & \cdots & \pi_{f(J)p_Jq_1} & \pi_{f(1)q_1q_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J)p_Jq_{J_\mathcal{B}}} & \pi_{f(1)q_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_{J_\mathcal{B}}} \end{bmatrix}^{-1} \begin{bmatrix} -\pi_{f(1)p_1\lambda} \\ \vdots \\ -\pi_{f(J)p_J\lambda} \\ -\pi_{f(1)q_1\lambda} \\ \vdots \\ -\pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}\lambda} \end{bmatrix}, \tag{20}$$

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 20 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 20, 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.