Subsidy design when firms can adjust product attributes: The case of electric vehicles*

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Abstract

This paper shows how subsidy design affects market outcomes in multi-product oligopolies when firms can adjust prices and product attributes. I show this in the electric vehicle (EV) market, which is characterized by subsidies and falling input prices. Using novel data from Germany, I estimate an equilibrium model of demand and supply of new cars. On the supply side, firms respond to subsidies by adjusting their electric vehicles' price and driving range. I find that the marginal cost of providing range decreased by 33% from 2012 to 2018. This decrease led to more expensive EVs with a greater range and a higher markup. Conversely, a subsidy introduced in Germany led to cheaper EVs with a smaller range and a lower markup. Finally, I compare different subsidy schemes and find that policymakers face a trade-off between maximizing diffusion, minimizing CO2 emissions, but can address distributional aspects.

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1 Introduction

Designing a subsidy that achieves its goal requires knowledge of how firms react to the subsidy. The economics literature has extensively studied how firms with market power react to subsidies when firms can only adjust prices (Bulow and Pfleiderer, 1983; Stern, 1987; Weyl and Fabinger, 2013). In this case, we know the direction of the adjustment: firms respond by lowering prices. The magnitude of the reaction depends on the slopes of the demand and marginal revenue curves. When firms can also adjust product attributes in response to a subsidy, the directions of the price and attribute adjustments are unclear. There exists no evidence in the economics literature on how firms in differentiated product markets adjust prices and product attributes in response to a subsidy.

Knowing what happens when responses by firms can be multi-dimensional is crucial for designing electric vehicle subsidies. Electric vehicles (EVs) play an integral role in reducing carbon dioxide emissions from the transportation sector, and thus countries have committed substantial amounts of funding for EV subsidies. In 2018 alone, world-wide government spending on EV purchases through subsidies totaled $15 billion.[1] The design of these subsidies differs across countries, with some basing subsidies on product attributes and others granting a subsidy with the same amount to every EV. Policymakers have several objectives in mind when designing these subsidies: minimizing CO2 emissions from new car sales, maximizing diffusion, and attending to distributional concerns. One feature of EVs is that firms can adjust the driving range relatively easily, giving them an additional dimension along which to react to subsidies.[2] The primary determinant of the range is the size of the battery pack and the propulsion mechanism of an EV. Another feature of EVs is that prices of lithium-ion cells, an essential input for battery packs, have dropped substantially over the past decade. This decrease has made the battery pack less expensive and has decreased the cost of providing range.

In this paper, my research question is as follows: How does subsidy design affect market outcomes when firms can adjust prices and product attributes? I use a novel state-level data set of new car purchases in Germany to estimate a structural model of demand and supply. The model allows for flexible substitution patterns across cars of different engine types on the demand side and endogenous range choices by firms on the supply side. I use the estimated model to assess a rich set of counterfactuals. First, I evaluate the impact of lower battery pack prices on the marginal cost of providing range and market outcomes. The supply estimates show that the marginal cost of providing range decreased by 33% from 2012 to 2018 and led firms to sell EVs at higher prices and with a greater range. Firms also collected a higher markup

[1] Source: International Energy Agency.

[2] The driving range, or range henceforth, is the distance that can be driven with a fully charged battery (or, in the case of combustion cars, with a full tank).

on these EVs. Second, I evaluate a subsidy scheme introduced in Germany in 2018 and find that it led to lower prices and a smaller range for electric vehicles on which firms collected a lower markup. Third, I evaluate the effect of different subsidy schemes on market outcomes. Purely range-based subsidies increase price and range, whereas flat subsidies decrease price and range. Policymakers face a trade-off in maximizing diffusion, minimizing CO2 emissions, but can address distributional aspects. Consumers prefer schemes purely based on the driving range of EVs, even though this result hides important distributional effects. Maximizing diffusion and minimizing CO2 emissions from new cars are not equivalent because achieving these two targets requires different substitution patterns. A policymaker can design subsidies that attain one of the objectives or achieve some combination of higher consumer surplus, lower fleet emissions, and greater diffusion.

Several challenges exist in analysing how a multi-dimensional reaction to subsidies and marginal cost changes affects outcomes. First, there exists little guidance in the existing literature on the effect of subsidies in multi-product oligopolies when firms can adjust prices and product attributes. Second, answering this question in the electric car market requires a demand model with rich substitution patterns between electric cars and combustion cars[3], given that the goal of electric vehicle subsidies is to generate more substitution towards electric vehicles. Third, the supply model should allow firms to react to a subsidy by adjusting not only the price but also the range of electric cars. My framework addresses these challenges. I estimate a structural model of demand and supply for new cars. On the demand side, consumers exhibit heterogeneous preferences for cars with different engine types. On the supply side, firms compete in a static oligopoly in which they set the prices of all their products and the range of their electric cars. In general, this model provides a framework for studying the impact of subsidies and marginal cost changes on the price and an adjustable product attribute in multi-product oligopolies. The model builds on Berry, Levinsohn, and Pakes (1995) and the recent literature studying equilibrium outcomes when firms can adjust one or more product attributes (Fan, 2013; Crawford, Shcherbakov, and Shum, 2019). I estimate the model using the generalized method of moments (GMM), using approximations to optimal instruments (Chamberlain, 1987) as proposed by Gandhi and Houde (2019).

Given parameter estimates, I first study the important reduction in prices of lithium-ion cells, a key input for battery packs, which determine the driving range. This input price drop is a defining feature of electric car markets. My framework allows both endogenous provision of range and a multi-dimensional response in terms of price and range to changes in the marginal cost of providing range. I find that the marginal cost of providing range decreased by 33% from 2012 to 2018. Firms pass on this negative shock to the marginal cost of range by selling EVs with a greater range at higher prices. The markup on electric cars increases. These

[3] Combustion cars employ a conventional gasoline or diesel engine to propel the car.

findings are important for subsidy design, as a decrease in the marginal cost of providing range is equivalent to a subsidy purely based on range. Moreover, pass-through occurs through the product attribute channel rather than the price channel. This finding underscores the importance of accounting for a channel through which car manufacturers can adjust range.

In 2016, Germany introduced a subsidy scheme for electric vehicles. The scheme consisted of a flat subsidy, meaning that the amount did not depend on any product attributes. My findings show that the subsidy led to both price and range decreases for electric vehicles, with firms collecting a lower markup. These outcomes are the converse of the adjustment that occurs in response to a lower marginal cost of providing range. In this case, pass-through occurred mainly through the price channel. Prices decreased by more than the amount of the subsidy. Firms used the product attribute channel to reduce range to allow for further price reductions. These two counterfactual exercises bracket the alternative subsidy schemes that I consider in the next step. These alternative schemes consist of a flat part and an incentive-based part that depends on range. The first two counterfactual exercises also make clear how different strategies shape market outcomes: On the one hand, firms can have incentives to increase price and range to target consumers with a high willingness to pay for range and thereby collect a larger markup. On the other hand, firms can have incentives to sell a cheaper product at a lower range, thereby collecting a lower markup but also capturing many consumers with a low willingness to pay for range. Finally, firms can use a subsidy to decrease price and increase range. Which adjustment strategy firms use shapes substitution patterns and, ultimately, market outcomes.

The estimated model allows me to compare a wide range of subsidy schemes and their impact on market outcomes. Across different budgets, I compare schemes that are either flat, are purely dependent on range, or mix a flat part with a range-dependent part. The market outcomes that I focus on are CO2 emissions from new cars and diffusion. In addition, I investigate the effects of subsidy design on consumer surplus and distributional aspects. The ultimate goal of policymakers is to de-carbonize the automobile sector; this makes it natural to look at CO2 emissions from new cars. At the same time, policymakers are interested in increasing diffusion to establish EVs on the market. Dynamic considerations related to learning curve effects also play a role. I find that flat subsidy schemes maximize diffusion. However, maximizing diffusion is not equivalent to minimizing CO2 emissions from new car sales. For the lowest budget considered, CO2 emissions from new cars are lowest at intermediate schemes. Differences in substitution patterns across different subsidy schemes drive this result. Maximizing diffusion warrants a subsidy that maximizes substitution from all cars, whereas minimizing emissions warrants a subsidy that induces more substitution from more-polluting cars. Moreover, I find that the pure range-based scheme maximizes consumer surplus. However, this finding hides substantial heterogeneity: Consumers in lower income deciles prefer purely flat schemes. They do so because the willingness to pay for range decreases with income, meaning consumers at the top of the income distribution have strong preferences for a greater range. In contrast, consumers at the bottom of the income distribution have strong preferences for lower prices. These findings suggest that policymakers can achieve different objectives with different subsidy schemes, with a trade-off in maximizing diffusion, minimizing emissions, and addressing distributional aspects. It is crucial to know how a given scheme affects substitution patterns. Otherwise, the subsidy may have unintended consequences. The results also suggest that a subsidy always decreases emissions, increases diffusion, and raises surplus for every consumer. Accordingly, it is always possible for a policymaker to achieve a combination of lower emissions and higher diffusion while leaving all consumers better off.

This paper contributes to different branches of the literature. The first contribution is to the literature on quality provision (Spence, 1975; Sheshinski, 1976; Mussa and Rosen, 1978; Maskin and Riley, 1984; Crawford et al., 2019; Holland, Mansur, and Yates, 2020) that studies how firms provide a product attribute (quality) in imperfectly competitive markets. The paper also contributes 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. This paper bridges a gap between these two literature streams by building 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.

This paper also contributes to the literature evaluating environmental policies in car markets. This literature studies how different environmental policies shape market outcomes and compares the effectiveness of different policy tools (Knittel, 2011; Klier and Linn, 2012; Pavan, 2017; Grigolon, Reynaert, and Verboven, 2018; Durrmeyer and Samano, 2018; Reynaert, Forthcoming; Leard, Linn, and Springel, 2019). A sub-branch of this literature is explicitly concerned with the EV market, studying the effect of EV subsidies (Beresteanu and Li, 2011; Xing, Leard, and Li, 2019; Muehlegger and Rapson, 2020) or the impact of charging stations (Li, Tong, Xing, and Zhou, 2017; Li, 2019; Springel, 2020). I contribute to this literature by studying the impact of battery cost changes, one of the defining characteristics of EV markets, on market outcomes. Further, this literature either assumes away supply-side responses of firms or constrains firms to adjust only prices in response to subsidies. This paper contributes to this literature by studying how firms adjust the range in response to subsidies, allowing for an explicit range adjustment channel in the supply model. Finally, I contribute to the literature studying subsidy schemes in EV markets by providing a detailed analysis of how different subsidy schemes affect firm strategies and policy objectives, giving rise to important trade-offs not considered in the literature so far.

2 Industry Description and Data

The setting for the empirical analysis is the new car market in Germany. A predominance of combustion engine cars using gasoline or diesel as fuel has characterized this market over the past decades. Simultaneously, sales of electric vehicles increased more than twenty-fold between 2012 and 2018. I estimate both consumer demand for new cars and competition in price and range among firms using a detailed data set of new car transactions.

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 in this electric engine to 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 de-carbonize the transportation sector in pursuit of the goal to contain the rise of global temperatures to below 2°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.[4]. Global government spending on EVs increased substantially from \$1 billion in 2012 to \$15 billion in 2018.

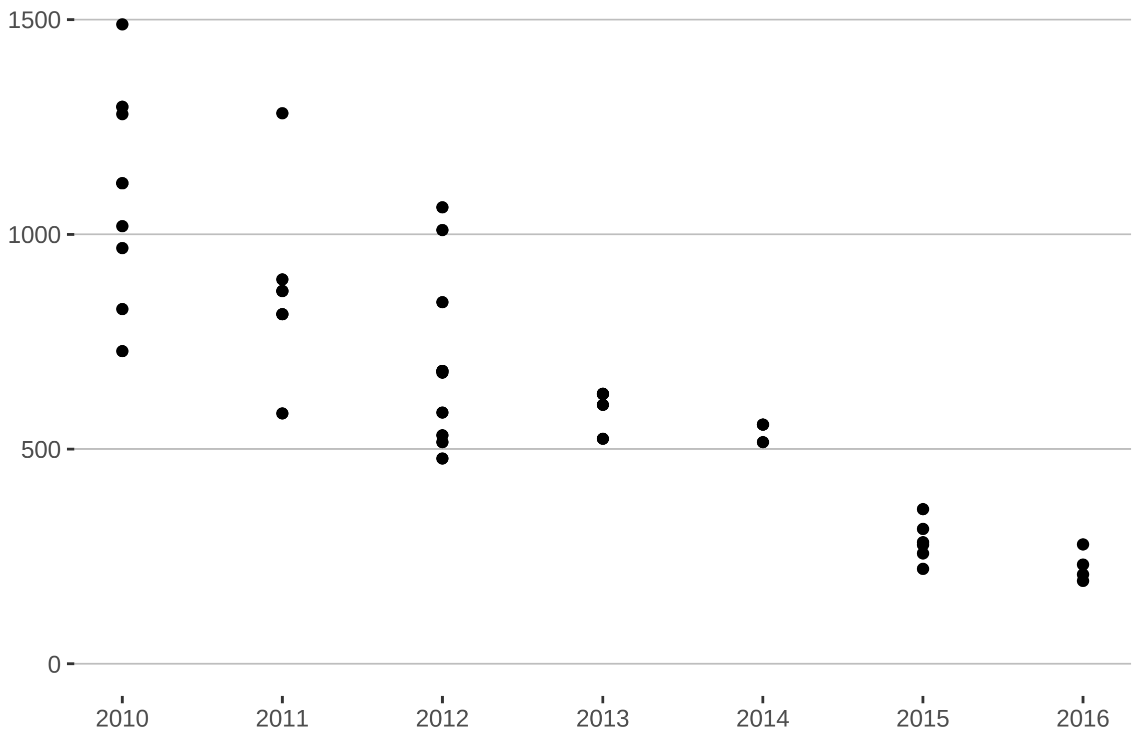
Another feature of the electric vehicle market is the rapid decrease in the cost of lithium-ion cells (LICs). Numerous LICs make up the battery pack of an electric vehicle. This battery pack propels the car, and its size is the most important determinant of the driving range. Figure 1 shows different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

[4] 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)



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).

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.[5] 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 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.[6] The plan reinforced the govern-

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

[6] Carmanufacturerspledgedtomatchthegovernmentsubsidybygrantingarebateequaltotheamountofthesubsidy.Theprogramalsoprovidedfundingfornewchargingstationsandvarioustaxbenefitsforbuying,using,andchargingelectricvehicles.https://www.bmwi.de/Redaktion/EN/Artikel/Industry/regula

ment's goal to have 1 million electric cars on the streets by 2020 and 6 million by 2030.[7] 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 lacklustre 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. 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.

Data

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

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

EV charging stations. I obtain the number of charging stations for electric car batteries from a publicly available data set listing all public charging stations from the Federal Network

tory-environment-and-incentives-for-using-electric-vehicles.html

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

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

Agency (BNetzA). The data set contains each station's opening date and its location. This data set allows me to build a variable counting the number of public charging stations in each state each year. I divide the obtained number of public charging stations per state and year by the state's population.

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 2 shows how the average price and range of battery electric vehicles developed during the sample period. Prices slightly increased, and the range rose by almost 60%. 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 7 of Appendix A.

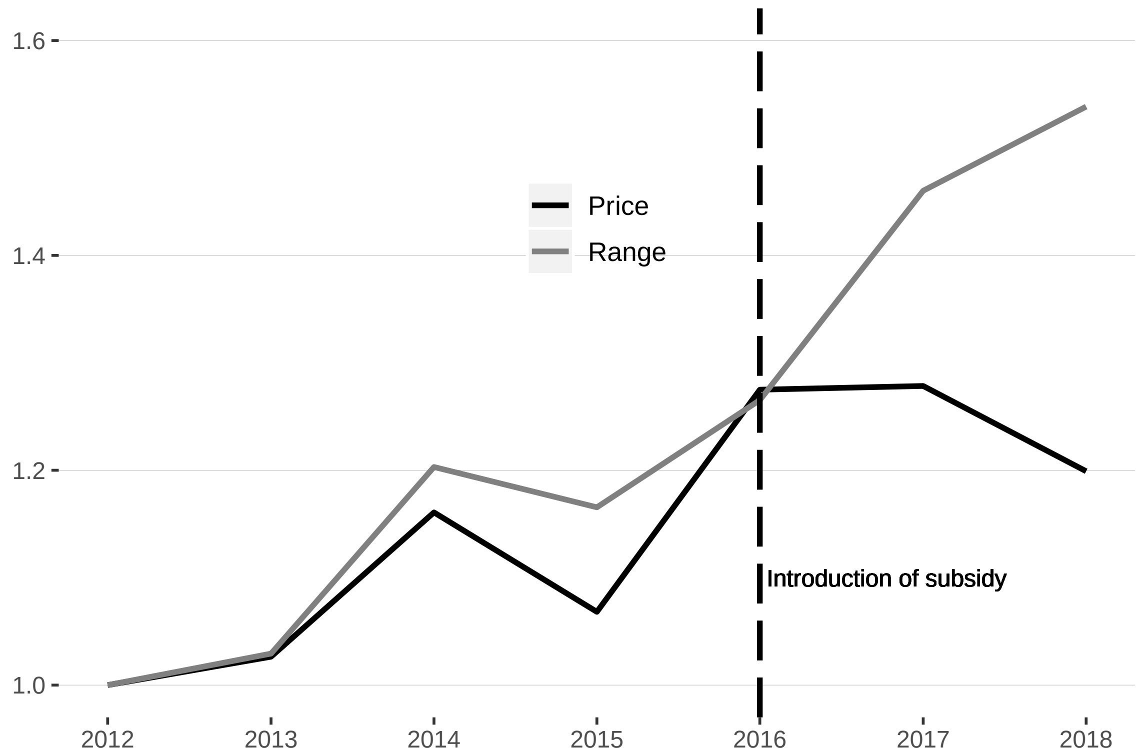
3 Empirical Model

Set-up

This section introduces a structural model of demand and supply for new cars under endogenous range choices. The model is close to those of Berry et al. (1995), Fan (2013), and Crawford et al. (2019). I need a model that generates realistic substitution patterns between electric cars and combustion cars on the demand side and that explains how firms choose range in a multi-product oligopoly on the supply side. 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.

Consumers choose the product maximizing their indirect utility and exhibit heterogeneous

Figure 2: Evolution of price and range of battery electric vehicles (averages, base = 2012)



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. These assumptions mirror evidence from consumer surveys on purchase behaviour and consumer preferences regarding battery electric vehicles. Several consumer surveys have found that driving range is the most critical consideration in the purchase of an electric vehicle, next to the price and charging station availability.[9] Additionally, the driving range of combustion engine cars is sufficiently high, and the network of gas stations is sufficiently dense. Hence, this characteristic does 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

[9] 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.

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.[10]

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

$$u_{ijmt} = r_{jt}\beta^r - \alpha \frac{p_{jt}}{y_{imt}} + x_{jmt}\beta_i^x + \xi_{jmt} + \varepsilon_{ijmt}, \tag{1}$$

where r_{jt} is the range of product j, 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, 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. The utility from purchasing the outside option is normalized to $u_{i0mt} = \varepsilon_{i0mt}$.

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

[10] The battery of a PHEV needs to work in conjunction with a combustion engine. This set-up 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.

characteristics:

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

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 $s_{mt} = s_{mt}(p,r,x,\xi;\sigma)$ for each market mt.

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.

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:

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

where $\phi_{mt} = \frac{\mathcal{M}_{mt}}{\sum_{m'} \mathcal{M}_{m't}}$ is the weight of state m, $\mathcal{J}_{ft}$ 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

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

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

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

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

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 rangey 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

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

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.

4 Estimation

Instrumental variables

Demand side

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 unobservables. The utility function also includes the number of charging stations available to electric vehicles. The charging station network is itself likely to depend on the electric vehicle base, creating an endogeneity issue (Pavan, 2017; Springel, 2020; 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.

Supply side

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, guaranteeing their exogeneity with respect to the unobserved range-specific cost shock. As on the demand side, I use a subset of the instruments that I create.

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 behaviour, 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 additional 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).

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.[11] 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

[11] Li (2019) uses a Bayesian shrinkage estimator to move market shares away from zero. Lu, Shi, and Gandhi (2019) 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 (2020) use a pairwise-differencing approach to estimate demand parameters.

and detailed discussion on this.[12]

Estimation of the 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.[13] 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 $E[z^d_{jmt}\xi_{jmt}] = 0$, with z^d_{jmt} as an instrument. Stacking ξ_{jmt} across products and markets into a column vector ξ, I obtain the GMM objective function to be minimized:

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

where Z^d contains the instruments and W^d is a positive definite weighting matrix. I use the two-step efficient GMM estimator, where I use an approximation of the optimal weighting matrix based on an initial set of estimates to recover the final estimated vector of parameters. The estimation algorithm that I use is described in detail in Berry et al. (1995) and Nevo (2001). In the estimation, I account for various numerical issues that recent literature has drawn attention to (Dubé, Fox, and Su (2012), Knittel and Metaxoglou (2014), Brunner, Heiss, Romahn, and Weiser (2017), Conlon and Gortmaker (Forthcoming)). First, I approximate the market share integral with 1,000 draws using modified Latin hypercube sampling. Hess, Train,

[12] 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 $q_j = 1$), which I see as evidence that my demand parameters are consistently estimated and lead me to believe that the correction I use is sufficient.

[13] 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.

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.

Estimation of the 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 additional 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.[14] 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.

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. The full estimation results including fixed effects are in Appendix B. Table 8 in Appendix A reports the first stage. Overall, the signs and magnitudes of the estimated coefficients are in line with standard economic intuition.

Table 1: Key demand and marginal cost estimates

Utility			**Marginal Cost**		
	Coefficient	SE		Coefficient	SE
Mean Utility			**range Provision**		
range	1.772	(0.223)	Intercept	0.813	(0.026)
range × Trend	-0.118	(0.024)	Trend	-0.070	(0.006)
Charging Stations	0.610	(0.156)			
Fuel Cost	-0.281	(0.027)			
BEV	-8.285	(1.539)			
PHEV	-5.901	(1.482)			
Interactions					
Price/Income	-5.713	(0.691)			
Standard Dev.					
EV	2.563	(0.685)			
Fuel Cost	0.134	(0.017)			
Statistics					
Mean own-price elasticity	-3.267				
Mean own-range elasticity (BEVs)	2.854				
Mean markup (€1,000)	10.556				

Note: Prices are deflated and in €1,000. Vehicle class, body, firm and state fixed effects included. See Appendix B for the full estimates.

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

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

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 Table 2. 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, 2020). The mean range elasticity is equal to 2.854.

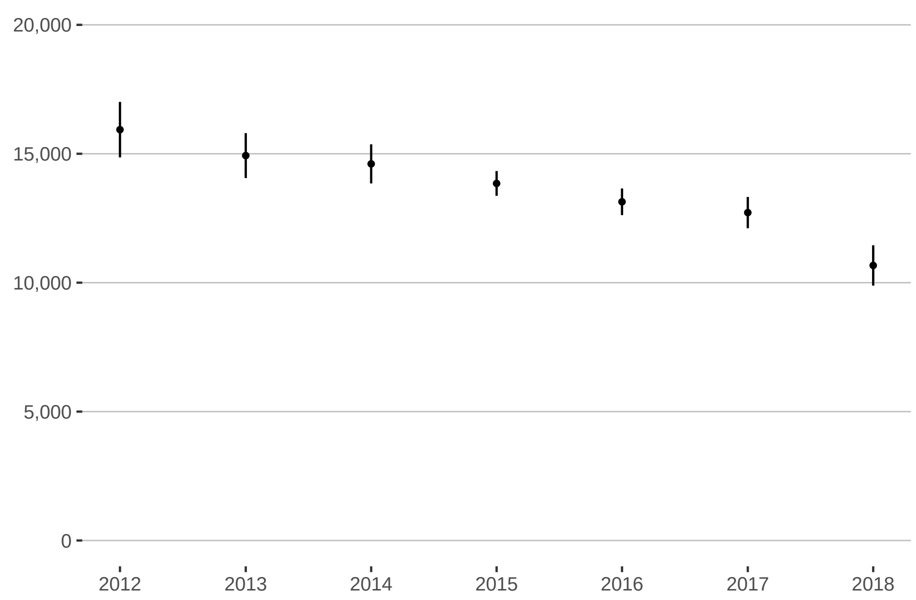
The negative and significant coefficient on price over income translates into a mean price elasticity of -3.267, which falls within the range of figures found in the long literature on demand estimation for new car markets. Table 12 in Appendix D shows how my estimated price elasticity compares to those 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. Graphical evidence of the findings is provided in Figure 9 in Appendix A. 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.

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 prefer electric cars over those with a combustion engine. The results suggest that the dis-utility 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.

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 behaviour, and preferences for less fuel-efficient cars play a role in shaping an individual's fuel cost valuation.

Figure 3: Estimated yearly mean marginal cost of providing range

Vertical lines are 95% CIs



On the marginal cost side, I find that range is costly to provide. range provision became cheaper over the sample period, evidenced by the trend's negative and statistically significant coefficient. This trend translates into a mean decrease in the marginal cost of providing range of approximately 33% from 2012 to 2018 (see Figure 3). This number is somewhat lower than the estimates of lithium-ion cell price decreases in Hsieh et al. (2019), for instance. Given that car manufacturers import most lithium-ion cells from overseas and may not directly benefit from price drops due to long-term contracts, it seems plausible that the fall in the marginal cost of providing range follows the lithium-ion cell price decrease less than one to one. Another explanation is that firms need to convert the lithium-ion cells into a battery pack that is an important – but not the exclusive – determinant of driving range.

Figure 4 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 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 4: Estimated marginal cost functions for 2012 and 2018

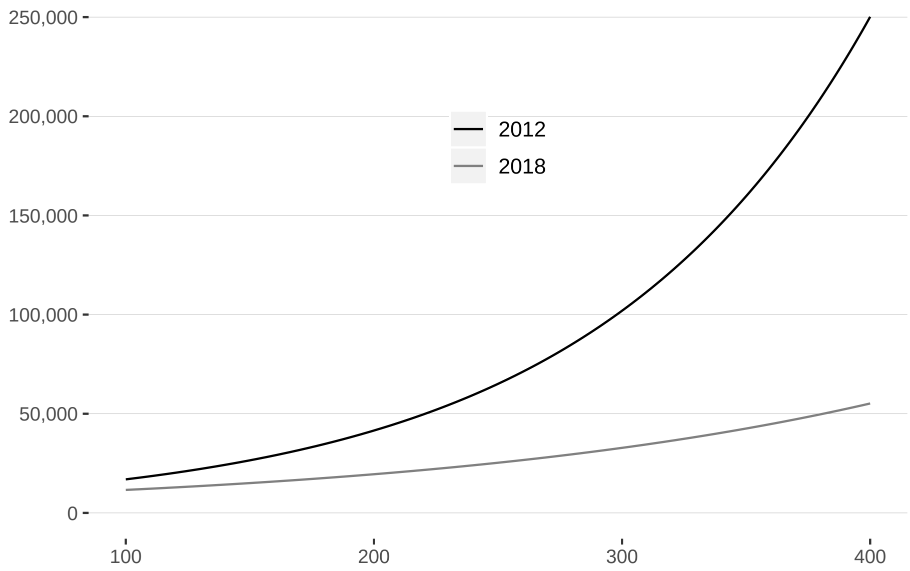
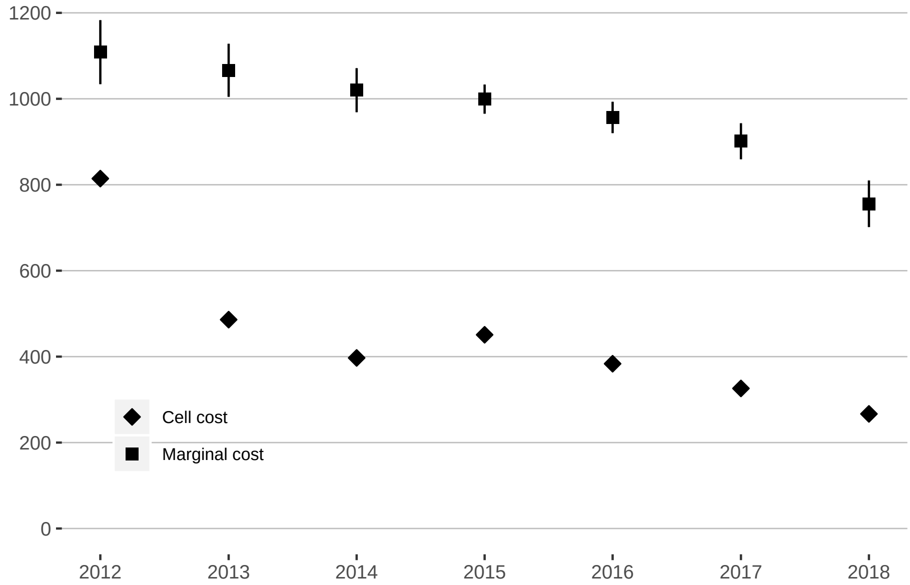


Figure 5: Per-kWh cost at observed range levels against battery pack cost



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 5. 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 in 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.

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 evaluate how firms use a lower marginal cost of providing range to adjust the price and range of their BEVs. In a second step, I assess the subsidy scheme imposed in Germany to see how firms adjusted price and range in response to the subsidy. 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.

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, I can compute the new equilibrium vectors of price and range. I employ an iterative algorithm to find the new equilibrium vector of prices and range levels $(\mathbf{p}, \mathbf{r})$. I proceed as follows: At iteration h,

1. Use the price FOCs to compute $\mathbf{p}^{h+1} = \mathbf{mc}(\mathbf{r}^h) + \Delta_p^{-1}\mathbf{s}(\mathbf{p}^h, \mathbf{r}^h) - \boldsymbol{\lambda}$

2. Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{r}^h$

3. Use the range FOCs to compute $\mathbf{r}^{h+1} = f(\mathbf{r}^h, \mathbf{p}^{h+1})$, where $f(\cdot)$ is the expression of range from (9).

4. Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{r}^{h+1}$

5. Let $d_{max} = \max(d_p^h, d_r^h)$, where $d_p^h = \max|\mathbf{p}^{h+1} - \mathbf{p}^h|$ and $d_r^h = \max|\mathbf{r}^{h+1} - \mathbf{r}^h|$

6. If $d_{max} \geq \epsilon^c$ with ϵ^c being some convergence criterion, go back to step 1. If $d_{max} < \epsilon^c$, extract $(\mathbf{p}^{h+1}, \mathbf{r}^{h+1})$ to be the new equilibrium vector of prices and range levels.

I adapt the algorithm for counterfactuals in which only price or only range is allowed to be re-adjusted simply by using the respective FOCs only. I find that this procedure converges to the same vector of prices and range levels even when I start from different starting values in different counterfactual settings, which I take as a sign that there exists a unique counterfactual equilibrium. Altering the ordering of the price and range updating does not change the results. The same holds for an alternative procedure, where I iterate until convergence on, say, price in an "inner loop" before iterating until convergence on the range and repeat both iterations until the "outer loop" converges. These alternative procedures give me confidence that the counterfactual results that I find are robust to the specific 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. Additionally, the first-order price changes are confined to BEVs. These factors contribute to the good convergence properties of the algorithms. I perform all counterfactuals for 2018.

How does a lower marginal cost of range provision affect price and range?

On the supply side of my model, I find that the marginal cost of range provision decreased by approximately 33% between 2012 and 2018. Evidence from the engineering literature and from policy reports suggests that a primary driver of this marginal cost drop has been falling lithium-ion cell prices. While there is uncertainty on the future path of these prices, there is a general agreement that they will continue to fall over the next 5-10 years (Hsieh et al., 2019; Nykvist and Nilsson, 2015; Green, Armstrong, Ben-Akiva, Heywood, Knittel, Paltsev, Reimer, Vaishnav, Zhao, Gross et al., 2019).

Table 2: Market outcomes with lower marginal cost of range

	Observed	**With lower marginal cost**		
	Base	Price, range adjust	Only price adjusts	Only range adjusts
Price	34,671	+659 (+584, +808)	-357 (-468, -226)	0
Range	259	+7 (+6, +15)	0	+3 (+3, +4)
MC	26,023	+554 (+482, +690)	-301 (-393, -192)	+59 (+54, +65)
Markup	10,536	+104 (+102, +123)	-56 (-81, -35)	-59 (-65, -54)
Sales	34,761	+594 (+290, +811)	+1,044 (+700, +1313)	+1,057 (+790, +1287)

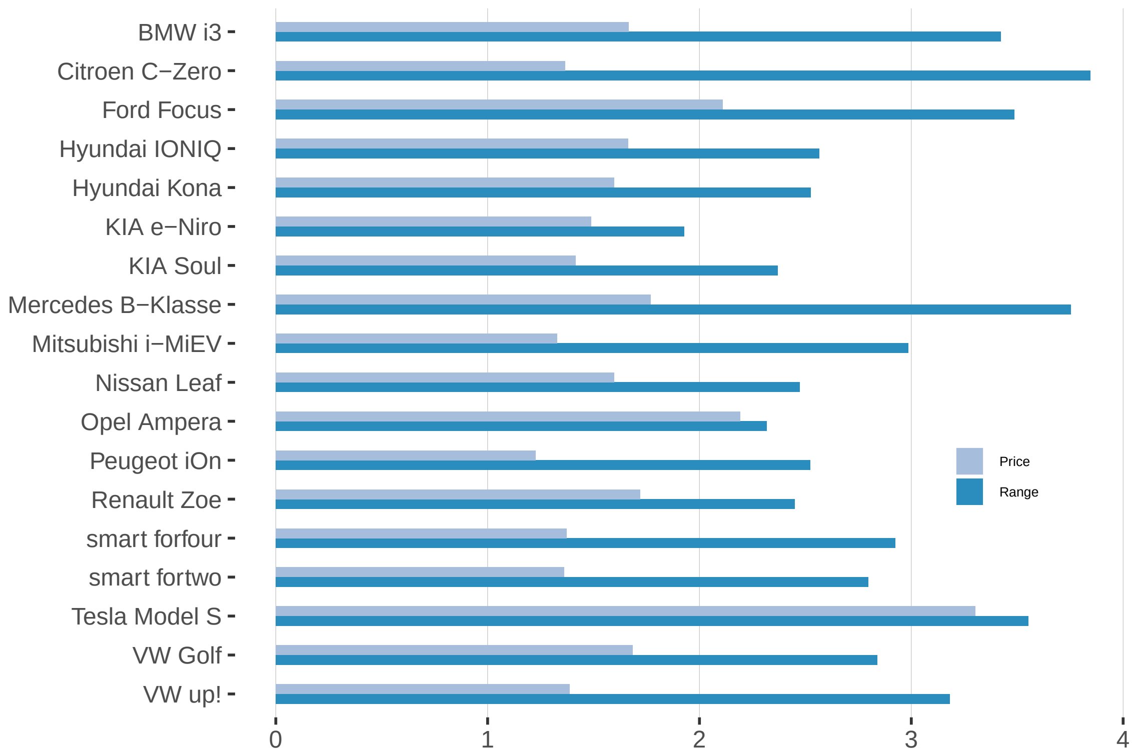
Notes: The table gives mean differences from observed outcomes with 95% CIs in parentheses.

In principle, firms can pass through lower marginal costs to price or range. The pass-through rates are given by $\frac{dp}{dc_1}, \frac{dr}{dc_1}$, where c_1 denotes the marginal cost of providing range. The signs and magnitudes of the rates are determined by the relative price and range semi-elasticities, the marginal cost of providing range, cannibalization effects, and the strategic effect of firms' own actions on rival firms. To find the direction and magnitudes of the effects, I re-compute the market equilibrium when the marginal cost of providing range drops by 1%.
I perform this counterfactual under three scenarios. In scenario 1, I allow firms to adjust prices and range. In scenarios 2 and 3, I restrict firms to adjusting price only and adjusting range only, respectively. The results are shown in Table 2.

The observed outcomes are in the second column of the table. The third column shows the results when the marginal cost of providing range decreases by 1% and both price and range can be adjusted. We can see that instead of passing through the cost decrease to lower prices, prices increase. The reason for this price increase is that firms improve range. Firms now sell a more expensive product with a higher range. The markup increases as well, suggesting that it is a profit-maximizing strategy to emphasize the intensive margin (charging a higher markup on existing consumers) over the extensive margin (attracting additional consumers). In other words, the firm finds it more profitable to attract consumers with a high willingness to pay for range as opposed to consumers who care relatively more about price than about range. In the last line of Table 2, we see that sales also increase by approximately 1.5%. Figure 6 shows that the direction of the effects is uniform across battery electric vehicles sold in 2018.

The third and fourth columns of Table 2 present the outcomes when only price and only

Figure 6: Percentage changes of price and range due to lower marginal cost of range



range can adjust, respectively. In the case of pure price adjustment, the average price decreases by approximately €357 or 1.03%, meaning that there is a slight over-shifting of the marginal cost drop. In the case of pure range adjustment, the average driving range increases by 3 km or 1.15%, also suggesting over-shifting. We can also observe that when firms can only adjust a single variable, the markup decreases, as opposed to the case where both range and price are free to change, suggesting that competitive effects are important. The ability to adjust both price and range allows firms to increase their markup, something that they do not find it profitable to do when they can only adjust price.

This section provides an answer to the question of how a marginal cost shock affects the price and range of battery electric vehicles: A negative marginal cost shock increases both prices and range levels, leading to more expensive products with higher range on which firms collect a higher markup. This result suggests that range can be expected to increase. However, this result depends on the current levels of price, range, and marginal cost of providing that range. When price, range, and the marginal cost of providing range are different, the directions and magnitudes of the effects of a lower marginal cost of providing range on price and range may differ.

How did the German subsidy scheme affect price and range?

The German government introduced a subsidy for electric vehicles in 2016. The goal was to increase diffusion 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 subsidy on the prices and range levels of battery electric vehicles. To do so, I re-compute the market equilibrium in 2018 without the subsidy. As in the case of a shock to the marginal cost of providing range, it is unclear how firms adjust the price and range of their products.[15] There also exist reasons to think that the response to a subsidy may be different from the reaction to a shock to the marginal cost of providing range: A subsidy is equivalent to a decrease in the total marginal cost of producing a product and not specific to particular adjustable product characteristics.

The results are in Table 3 and show outcomes from three counterfactuals: Column 3 shows outcomes when both price and range are allowed to adjust. Columns 4 and 5 show outcomes where only price and only range are allowed to adjust, respectively.

Table 3: Difference in market outcomes without the subsidy

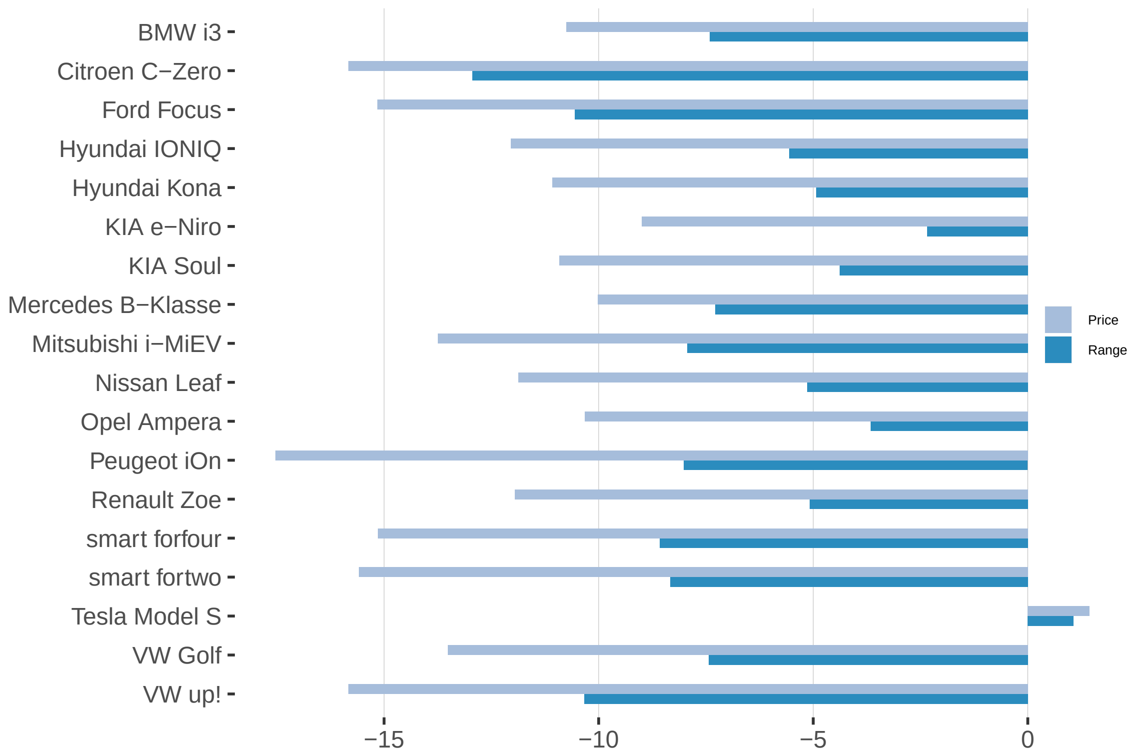
	With subsidy	**Without subsidy**		
	Base	Price, range adjust	Only price adjusts	Only range adjusts
Price	34,671	+4,099 (+3,806, +5,799)	+2,268 (+2,219, +2,316)	0
Range	259	+15 (+9, +30)	0	-13 (-21, -10)
MC	26,023	+1,522 (+1,235, +2,925)	0	-1,294 (-1,371, -1,195)
Markup	10,536	+688 (+292, +592)	+379 (+191, +352)	-595 (-672, -524)
Sales	34,761	-7,431 (-8,222, -6,571)	-6,707 (-7,422, -5,972)	-4,333 (-5,174, -3,547)

Note: The table gives the differences from observed outcomes with 95% CIs in parentheses.

We can see in column 3 that the predictions drawn from the comparative statics are validated. Without the subsidy, both prices and range levels would have been higher on average. The results suggest that on average, price pass-through was more than 100% (the subsidy was €2,000 in 2018). The pass-through rate to price was over 200%. Firms compensated for this over-shifting by lowering the range. Markups also fell in response to the subsidy, meaning that firms sold cheaper cars with less range on which they collected a smaller markup. Column

[15] In Appendix E.2, I show how the system of first-order conditions can be used to predict the direction of the effects without having to perform a counterfactual analysis.

Figure 7: Percentage changes of price and range due to introduction of subsidy



4 suggests over-shifting of the subsidy in a counterfactual scenario in which firms were only allowed to adjust prices. The pass-through rate is approximately 113% in this case. This rate is slightly higher than that found by Muehlegger and Rapson (2020) for subsidies in California, where pass-through was indistinguishable from 100%. Column 5 indicates that if firms had only been able to change range, the subsidy would have led to an increase in range at a higher markup. In the last line of Table 3, we can see that the subsidy increased sales by 7,431 units or approximately 21%. We also see that not accounting for range adjustment leads to an under-prediction of the effect that the subsidy had on sales. In either case, we can conclude that the subsidy is far from generating the diffusion needed to achieve the goal of having 1 million electric vehicles on the streets by 2020. Figure 7 shows the product-level effects of the subsidy. We can see that firms decreased the price and range of all subsidized products, and the lone non-subsidized BEV, the Tesla Model S, saw an increase in both price and range in response to the subsidy.

Discussion

The analysis of marginal cost shocks and the subsidy makes apparent two countervailing forces in the market for battery electric vehicles: On the one hand, subsidies put downward pressure on prices, range, and markups. On the other hand, a lower marginal cost of providing range puts upward pressure on prices, range, and markups. The fact that the subsidy leads firms to sell cheaper cars with lower range and that a lower marginal cost of providing such range leads firms to sell more expensive cars with higher range suggests that substitution patterns from combustion cars, as well as the outside option, are different in the two cases. Knowing what substitution patterns look like and how they change in different scenarios is essential for subsidy design.

The countervailing effects of subsidies and a lower marginal cost of range can also help to explain the evolution of price and range over the sample period (see, e.g., Figure 2): Until the end of 2015, there was no subsidy in place, meaning that there was only upward pressure on prices and range levels, explaining the increasing slopes of both curves. Starting with the introduction of the subsidy in 2016, we see that prices first plateaued and then decreased, suggesting that the subsidy's negative price effect dominated the positive price effect of the marginal cost drop. The net impact on range stayed positive, even though the increase seems to have slowed down. Overall, the total effect depends on the amount of the subsidy, the magnitude of the marginal cost decrease, consumer preferences, and the current price and range levels. Based on these factors, the total effect of subsidies and changes in the marginal cost of range on price and range may be either positive or negative.

These results raise questions for policymakers regarding subsidy design. The findings suggest that a possibly unintended side effect of flat purchase subsidies is a lower range. On the one hand, using the support scheme to offer lower-range, lower-price products may be desirable for very price-sensitive consumers and allow firms to increase sales. The results from these two counterfactual exercises also raise the question of how a policymaker can achieve different objectives through subsidy design. At what level would consumer surplus be maximized? The ultimate goal of policymakers is to eliminate CO2 emissions from new cars sold to de-carbonize the transport sector. What subsidy scheme achieves minimal CO2 emissions from new sales? Finally, many governments have introduced sales targets for electric cars that they try to meet by maximizing diffusion. A diffusion-maximizing strategy may also make sense when policymakers have dynamic incentives, such as moving down a learning curve. In that case, it can be optimal to forgo emission savings now because moving down the learning curve quickly leads to higher diffusion and higher emission savings in the future. The next section investigates which subsidy schemes achieve different objectives and whether they are compatible with one another.

Incentive-based subsidies

Policymakers in different countries use different subsidy schemes. For instance, the total subsidy in California and China is a function of the driving range or the size of the battery pack (Rokadiya and Yang, 2019). In Germany, on the other hand, the amount does not differ across different EVs. In this section, I compare range-based schemes with schemes that are invariant across different models. In particular, I evaluate subsidies of the form $\lambda_j = \lambda_0 + \lambda_1 r_j$. Note that while simple, this scheme nests both the case of a flat subsidy and a decrease in the marginal cost of providing range. When λ_1 is zero, we recover a simple flat subsidy of the form implemented in Germany. When λ_0 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_0 and λ_1 are non-zero as putting weights on a general and a range-specific marginal cost decrease.

To find the budget-equivalent values for λ_0 and λ_1, I use the following procedure: At a given budget B, I search for values of λ_0, λ_1 that satisfy the budget constraint. I employ a grid search where at each candidate value $(\tilde{\lambda_0}, \tilde{\lambda_1})$, I solve for the counterfactual equilibrium vector of prices and ranges 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. I perform this search for different values of B: In the first search, B is equal to the observed subsidy scheme's cost in 2018 and subsequently increases in further searches. For each candidate point, I compute the mean price and range of BEVs, the quantity sold of BEVs, consumer surplus[16], and fleet emissions, computed as the sales-weighted CO2 emissions from new cars sold.[17] 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 de-carbonized. De-carbonized 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 behaviour.

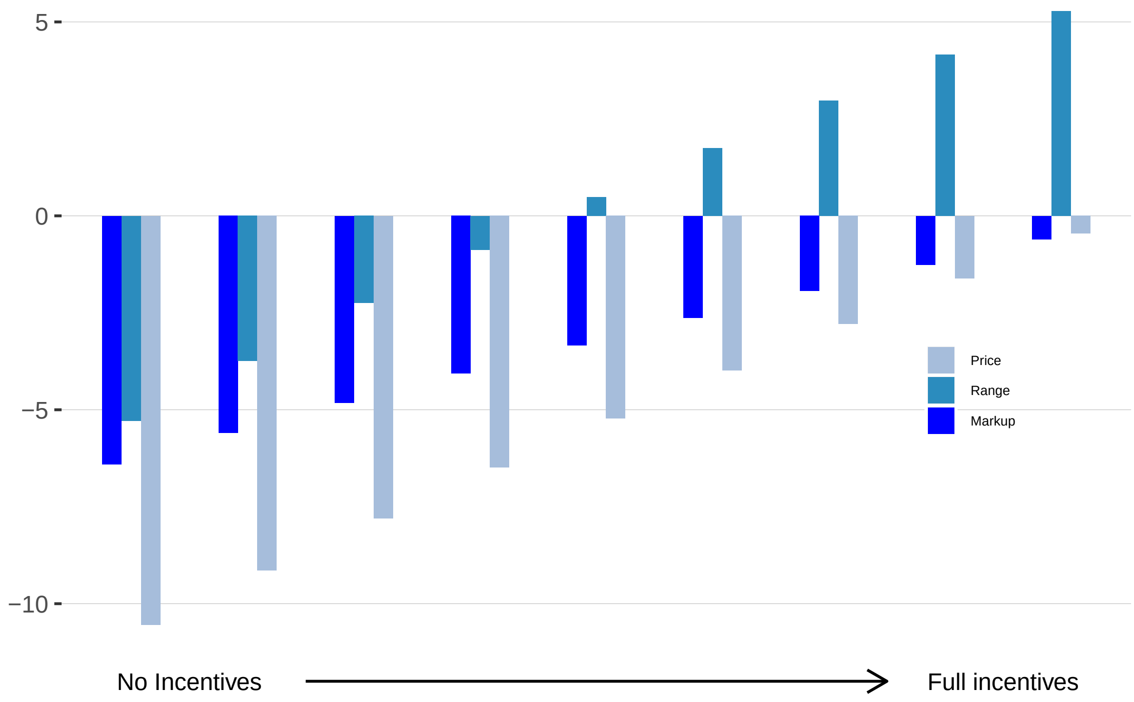
I focus on three outcomes in this section: First, I look at CO2 emissions from new car

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

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

Figure 8: Firm strategies across subsidy schemes

Mean percentage changes at lowest budget

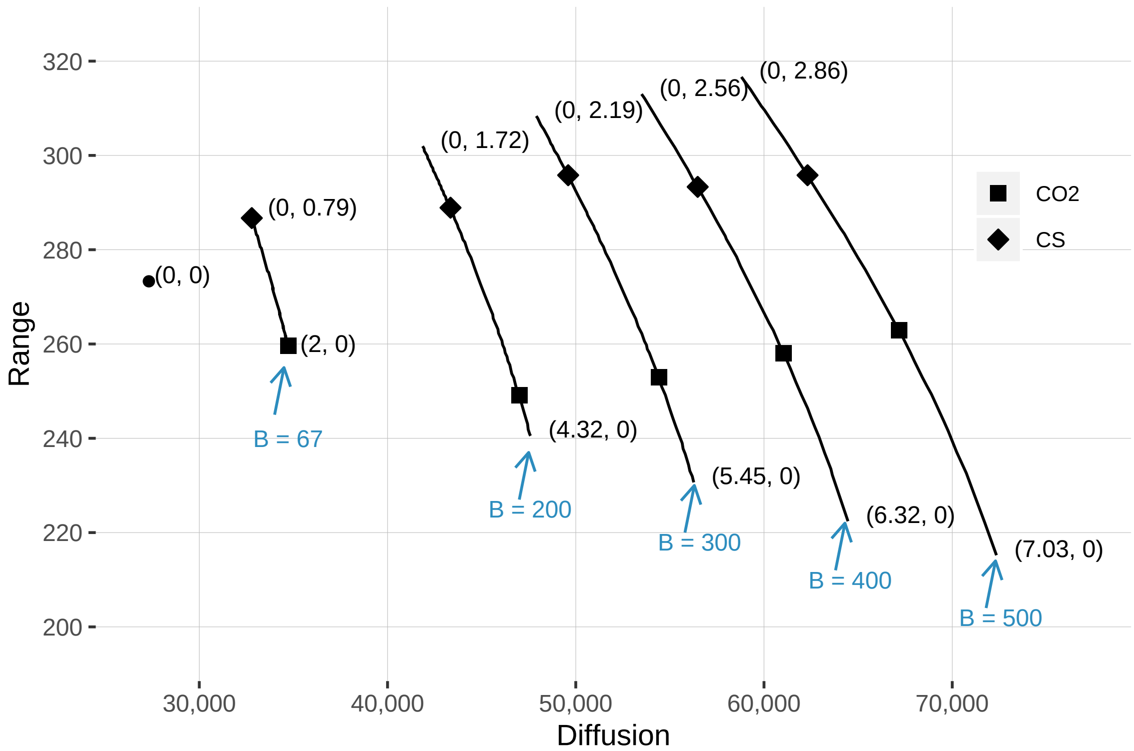


sales. Focusing on this target makes sense, as the ultimate goal of subsidizing BEVs is to de-carbonize the transport sector. The fewer vehicles emitting CO2 sold, the lower are the CO2 emissions from the existing vehicle stock. Second, I focus on diffusion. This target makes sense for two reasons. First, 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. Finally, I take into account distributional aspects by looking at consumer surplus along income deciles.

Firms adopt two strategies, depending on the subsidy's design: First, when the subsidy is flat, we recover the previous section's result: Firms decrease both price and range and collect a lower markup on their BEVs. Firms also employ this strategy when facing schemes with low-powered incentives on range. Second, when subsidies put more incentives on range, firms use a mix of lower prices and higher range. The decrease in markups is smaller, meaning that at

Figure 9: Policy outcomes at different subsidy schemes (λ_0, λ_1) and budgets

Subsidy in €1,000, budget in €million



schemes with stronger incentives, firms sell relatively more expensive BEVs with a higher range and a relatively higher markup. We do not recover the result from Section 6 that firms increase both price and range and earn a higher markup on their BEVs. Note that in Section 6, a (flat) subsidy is already in place. The decrease in the marginal cost is then akin to replacing the flat subsidy with a mixed scheme. Increasing incentives always increases range and markups and decreases prices. Figure 8 shows how firms react to different subsidy schemes when the budget is €67 million. While the magnitudes of the effects change at higher budgets, the pattern described above does not: Flat subsidies and low-incentive mixed schemes always lead to cheaper BEVs with a lower range on which firms collect a lower markup. Pure range-based and high-incentive mixed schemes always lead to relatively more expensive BEVs with a higher range on which firms collect a relatively higher markup. It is crucial to understand firms' strategic reactions to different subsidy schemes because these strategies lead to different BEVs on the market and different substitution patterns. These substitution patterns shape policy objectives such as emissions from new car sales and diffusion.

Policy outcomes

Figure 9 shows policy outcomes under different subsidy schemes. The plot shows iso-budget curves for different budget levels and the "initial point" without subsidies from Table 3. The black diamonds denote the subsidy scheme maximizing consumer surplus at a given budget, whereas the black squares represent the scheme minimizing fleet emissions at a given budget. We can see that the flat subsidy *always* maximizes diffusion, suggesting that lower-range, cheap BEVs induce the most substitution from other cars and the outside option. Also, we see that fleet emissions are minimized at intermediate schemes. Maximizing diffusion of zero-emission BEVs and minimizing fleet emissions are not equivalent. Minimizing emissions calls for different substitution patterns compared to those generated by a flat subsidy. More substitution from polluting cars makes up for the lower overall substitution. A mixed subsidy scheme placing some incentives on range provision achieves this substitution from more polluting cars. Finally, schemes with strong incentives on range always maximize consumer surplus. Consumers care more about range than about price in relative terms to prefer a market outcome at which BEVs have a high range at higher prices, rather than a market outcome where the opposite holds. Together, these findings show that maximizing diffusion, minimizing fleet emissions, and maximizing consumer surplus are mutually exclusive at any budget. The policymaker can achieve these two goals separately or accomplish a mix of these goals, as any subsidy scheme *always* increases consumer surplus, decreases fleet emissions, and increases diffusion.

Table 4: Substitution patterns by engine type

Budget:	**€ 64 million**			**€ 200 million**			**€ 300 million**			**€ 400 million**			**€ 500 million**		
	Diffusion	Range	CO2	Diffusion	Range	CO2	Diffusion	Range	CO2	Diffusion	Range	CO2	Diffusion	Range	CO2
Percentage															
Outside option	77.26	73.34	77.15	79.04	73.99	78.34	80.08	74.37	78.43	80.96	74.71	78.46	80.96	74.71	78.46
ICE	17.93	21.05	18.02	16.71	20.64	17.25	15.99	20.4	17.26	15.36	20.2	17.29	15.36	20.2	17.29
PHEV	4.8	5.61	4.83	4.25	5.37	4.41	3.93	5.22	4.31	3.67	5.09	4.24	3.67	5.09	4.24
Absolute															
Outside option	5,904	4,091	5,869	16,187	10,908	15,575	23,340	15,456	21,418	30,234	19,705	26,620	30,234	19,705	24,351
ICE	1,370	1,174	1,371	3,423	3,043	3,430	4,660	4,240	4,714	5,737	5,328	5,868	5,737	5,328	5,779
PHEV	367	313	367	870	792	876	1,147	1,085	1,177	1,372	1,343	1,439	1,372	1,343	1,433
Scheme															
λ_0	2,000	0	1,950	4,315	0	3,900	5,450	0	4,400	6,320	0	4,650	7,028	0	4,800
λ_1	0	750	25	0	1,720	210	0	2,188	542	0	2,555	866	0	2859	1,156

Percentage terms may not equal 100% due to rounding errors.

Table 4 shows substitution patterns from the outside option, combustion cars (ICEs), and PHEVs towards BEVs under the schemes maximizing diffusion and range, respectively, and minimizing fleet emissions (CO2) at the different budgets. We can see several patterns that help explain Figure 9: First, substitution from the outside option is always highest at the flat scheme and lowest at the pure incentive-based scheme. Second, substitution from the inside goods in relative terms is highest at the pure incentive-based scheme and is lowest at the flat scheme. Lower substitution from inside goods is more than made up for by higher substitution

Table 5: Market outcomes at different budgets, flat versus range-based subsidies

Budget:		**€ 64 million**		**€ 200 million**		**€ 300 million**		**€ 400 million**		**€ 500 million**	
	Base	Incentive	Flat	Incentive	Flat	Incentive	Flat	Incentive	Flat	Incentive	Flat
Sales	27,119	+5,578	+7,642	+14,742	+20,480	+20,782	+29,147	+26,377	+37,343	+31,680	+45,230
Range	273.16	+14	-14	+29	-33	+35	-43	+40	-51	+43	-58
Price	38,756	-178	-4,085	-816	-8,805	-1,286	-11,152	-1,721	-12,988	-2,123	-14,500
MC	27,538	+1,866	-1,515	+3,900	-3,254	+4,864	-4,125	+5,592	-4,816	+6,175	-5,392
Markup	11,218	-38	-682	-153	-1,476	-236	-1,879	-313	-2,201	-384	-2,470
Profits	30,792	+79	+81	+139	+147	+178	+189	+213	+227	+246	+262
λ_0	0	+790	+0	+1,720	+0	+2,188	+0	+2,555	+0	+2,858	+0
λ_1	0	0	2,000	0	4,315	0	5,450	0	6,323	0	7,028

from the outside good at the flat scheme, thus maximizing diffusion. It is a profit-maximizing strategy for firms to use a flat subsidy to sell cheaper products at a lower range. This strategy has a market-expanding effect and mainly attracts consumers who chose not to purchase a new car before. On the other hand, pure incentive-based subsidies make it profit-maximizing for firms to sell more expensive cars with a higher range. This strategy attracts consumers who value the higher range provided and previously purchased a non-BEV inside good. Firms use a similar strategy at high-incentive mixed schemes that maximize consumer surplus, suggesting that consumers, on average, have a relatively higher sensitivity to range than to price. Finally, Table 4 also explains why intermediate schemes (or the flat scheme for the lowest budget) minimize fleet emissions: Combustion cars have higher CO2 emissions than PHEVs. Together with the assumption that consumers who choose the outside option cause zero CO2 emissions[18], this means that fleet emissions will be lowest at the point where substitution from combustion cars is the highest. Maximal substitution from combustion cars occurs at mixed schemes.

Table 5 shows the market outcomes of the flat schemes and the pure incentive-based schemes at different budgets. When the budget is set to € 200 million, for instance, the flat subsidy ($\lambda_1 = 0$) leads to a 33km, 12%, decrease in range and a 76% increase in diffusion, or 20,480 cars in absolute terms. A pure incentive-based subsidy ($\lambda_0 = 0$), on the other hand, leads to a 29km, or 11%, increase in range but only a 55% increase in diffusion, or 14,742 cars in absolute terms. In other words, an extra 5,738 units "costs" the policymaker 62km of range, equal to around 23% of the range absent any subsidies. We can also see that the flat subsidy raises total firm profits by more than the pure incentive-based subsidy. The flat subsidy gives firms more flexibility in "interpreting" the subsidy: It is equivalent to a general decrease in the marginal cost of producing a BEV. In contrast, the pure incentive-based subsidy is equivalent to a decrease in the range-specific part of marginal cost.

[18]This assumes that the consumers attracted from the outside option did not use modes of transport emitting CO2 emissions before.

Table 6: Preferences for subsidy scheme across income deciles

Budget:	**€ 64 million**	**€ 200 million**	**€ 300 million**	**€ 400 million**	**€ 500 million**
Scheme					
Deciles preferring					
Flat	9	9	8	8	8
Mixed	0	0	1	1	1
Incentive	1	1	1	1	1
Marginal decile					
Flat to Mixed	-	-	8-9	8-9	8-9
Mixed to Incentive	-	-	9-10	9-10	9-10
Flat to Incentive	9-10	9-10	-	-	-

Distributional aspects

Table 5 makes clear that the market outcomes for BEVs are significantly different between the flat- and the pure range-based subsidy schemes. Flat schemes produce cheaper BEVs with a lower range, whereas incentive-based schemes create more expensive BEVs with a higher range. These two outcomes likely mean that different consumers buy BEVs in the two cases. The demand model results yield a lower price sensitivity from consumers with higher income, meaning that their willingness to pay for range is higher. This greater willingness to pay at higher income deciles suggests that consumer surplus alone hides important distributional effects. Table 6 illustrates these distributional effects. The table reports the number of income deciles preferring either a flat, a mixed, or a pure incentive-based scheme along with the "marginal deciles" between which preferences for different schemes switch. We can see that most income deciles prefer flat schemes, with only the top decile having a preference for pure incentive-based schemes. However, the gain in consumer surplus in this decile is enough to make overall consumer surplus maximal at schemes that put strong incentives on range. We can also see that preferences are very polarized in that only the 9th income decile has a preference for a mixed scheme (at a budgets over €200 million). In contrast, all other income deciles either prefer a flat or a true incentive-based scheme. These findings suggest that there are important distributional consequences to consider when designing subsidies. A policymaker can target different consumer segments with different schemes.

Discussion

These results suggest that at the observed levels of price, range and marginal cost in 2018, a policymaker interested in maximizing diffusion merely needs to introduce flat subsidy schemes. On the other hand, a policymaker interested in minimizing fleet emissions would take another strategy, employing a mixed scheme that maximizes substitution from more polluting combustion cars. A high-incentive mixed subsidy maximizes consumer surplus, even though this hides important distributional aspects. In summary, policymakers face a trade-off between diffusion, emissions, but can address distributional aspects. This suggests that a policymaker needs to be mindful when deciding on a policy objective as it may have unintended consequences on other outcomes. The results also suggest, however, that a policymaker can always achieve a mix of the three goals as a subsidy *always* increases consumer surplus for all consumers, *always* increases diffusion, and *always* reduces fleet emissions. What holds regardless of the level of prices, ranges, and marginal cost of range provision is that a policymaker intending to maximize diffusion with a subsidy should be mindful of the impact of price and range on firms' intensive and extensive margins. A subsidy can lead a firm to use three strategies, two of which we have seen in this section: First, a firm could use the subsidy to decrease both price and range. Second, the firm could use the subsidy to decrease price and increase range. Third, a firm could use the subsidy to increase both the price and range. These three strategies will generate different substitution patterns from polluting cars and the outside option, leading to different market outcomes.

The downward trend in the marginal cost of providing range puts upward pressure on price and range. As long as range provision continues to become cheaper, a flat or low-incentive subsidy's negative effect on the range is likely to be mitigated or even dominated by this range-enhancing effect.

For the German market studied here, the results suggest that flat subsidies were indeed diffusion maximizing, albeit with a moderate overall effect. The findings also indicate that increasing diffusion to a level that would bring the electric vehicle stock close to 1 million by 2020 necessitates a substantial increase in the subsidy amount.

This section's findings are also relevant to other markets: Policymakers often subsidize access to necessary infrastructures such as water and electricity in developing countries. These subsidies may have adverse effects on quality (McRae, 2015). Another example is newspaper markets, where quality may be affected by subsidies aimed at increasing readership numbers (Battaggion and Vaglio, 2018). In these cases, policymakers need to be mindful of relative preferences for price and quality, the cost of quality provision, and the impact of these factors on firms' intensive and extensive margins. Ultimately, a subsidy's effect on price and an adjustable product attribute is an empirical question that calls for a case-by-case evaluation. In general, this section shows that subsidy design in a multi-product oligopoly when firm reactions can be multi-dimensional can lead to very different strategic reactions by firms, affecting substitution patterns that ultimately shape market outcomes.

7 Conclusion

In this paper, I study how firms adjust the price and range of electric vehicles in response to subsidies and changes in marginal cost. Falling input prices and subsidies characterize the electric vehicle market. Even though understanding how input prices and subsidies are passed through to price and range and how they affect the diffusion of electric vehicles is essential for proper subsidy design, there is little evidence on pass-through when price and range are endogenous.

I develop a structural model of demand and supply for new cars, and estimate it using a novel data set on state-level new car sales in Germany. On the demand side, consumers choose between cars of different engine types. The demand side allows for rich substitution patterns across electric and combustion cars. On the supply side, firms compete in prices and can set the range of their battery electric vehicles (BEVs). The model provides a framework for analyzing the impact of subsidies in imperfectly competitive markets when firms choose the price and product attributes.

I find that the marginal cost of providing range has decreased by approximately 33% over the sample period. I use the estimated model to analyze how firms adjust price and range in response to cheaper range provision and subsidies. The lower marginal cost of range provision increased the price and range of BEVs, with firms collecting a higher markup. Conversely, a flat subsidy introduced in Germany led to cheaper BEVs with a lower range on which firms collect a lower markup. The subsidy increased sales by approximately 27% in 2018, far from sufficient to meet the governments' sales targets.

I then compare the flat subsidy imposed in Germany to alternative schemes used in other countries and their effect on policy goals. I find that policymakers face a trade-off between maximizing diffusion, minimizing emissions, but can address distributional concerns. Different substitution patterns at different schemes drive this result. These substitution patterns ultimately determine market outcomes. On the one hand, flat subsidies and schemes with low-incentive mixed schemes induce firms to employ a strategy of selling BEVs with less range at a lower price, capturing a large number of consumers on which firms collect a smaller markup. On the other hand, pure range-based subsidies and high-incentive mixed schemes induce firms to sell BEVs with more range at a relatively higher price, attracting consumers with a high willingness to pay on which firms collect a relatively higher markup. The findings suggest that a policymaker can always achieve a mix of the three policy goals as the subsidies always increase consumer surplus and diffusion and always decrease fleet emissions.

This result also has direct implications for distributional effects: As consumers with a higher income have a higher willingness to pay for range, they are better off under high-incentive schemes. Consumers in lower-income deciles, to the contrary, are better off under a flat subsidy scheme. On the one hand, there may be important distributional effects from different subsidy schemes. On the other hand, targeting specific consumer groups can be compatible with a given policy objective. The diffusion-maximizing subsidy scheme coincides with the scheme maximizing consumer surplus for lower-income groups, for instance.

The results have implications for policymakers. It is crucial to understand substitution patterns generated by different subsidy schemes. Consumer preferences ultimately drive these substitution patterns for range and price and the marginal cost of providing range. These insights generalize to other markets in which firms can adjust one or more product attributes in response to subsidies.

My paper leaves scope for future work. First, I do not directly explore dynamic incentives that may exist due to learning effects. Second, I take the product portfolio of firms as given. Recent years have seen the introduction of a large number of new EV models. Endogenizing the product portfolio may be necessary to understand how firms react to subsidies and cost changes by (not) introducing new products. Finally, firms have been increasingly offering models with different range specifications. Firms offering menus of price and range add an angle to range provision as firms may distort price and range within their menu.

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A Additional Figures and Tables

Table 7: Summary statistics

Mean values of key characteristics

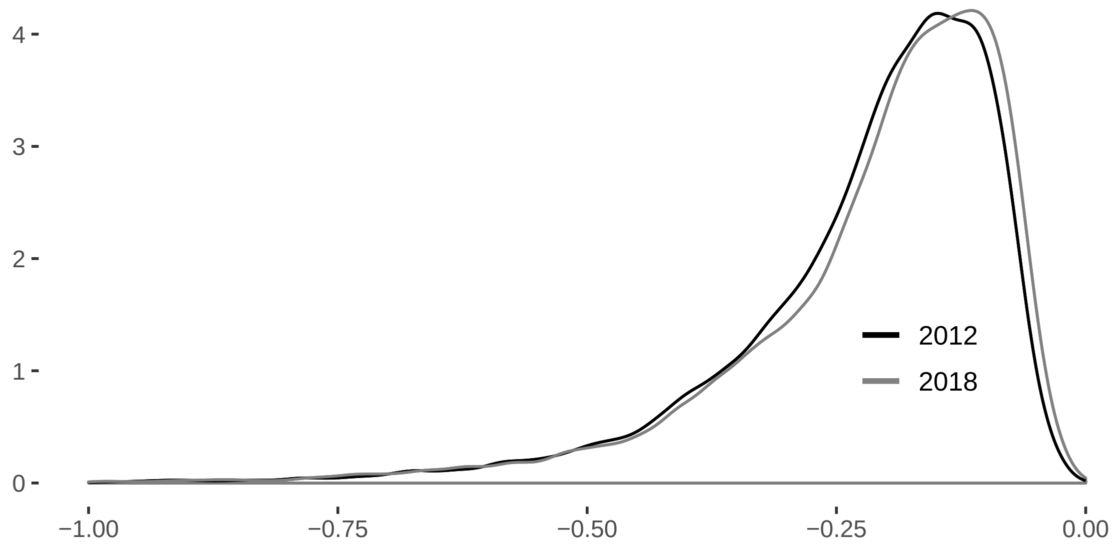
Variable	2012	2013	2014	2015	2016	2017	2018
BEV							
Price	30,490	31,295	35,392	32,569	37,104	37,200	34,671
Range (in km)	168	173	202	196	213	246	259
Fuel Cost	4.02	4.34	4.37	4.19	4.24	4.28	4.21
Acceleration	2.8	2.98	3.19	2.96	3.31	3.26	2.94
Weight	1,581	1,662	1,797	1,797	1,867	1,902	1,841
Footprint	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 8: First Stage Estimates

	Price		Range		Range x Trend		Stations	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Exogenous Charac.								
Fuel Cost	-0.603	(0.025)	0.000	(0.000)	0.005	(0.002)	0.001	(0.001)
Footprint	4.149	(0.121)	0.065	(0.003)	0.248	(0.018)	-0.001	(0.004)
Acceleration	2.886	(0.044)	-0.024	(0.002)	-0.118	(0.011)	-0.004	(0.002)
Doors	1.279	(0.075)	-0.035	(0.002)	-0.175	(0.010)	-0.002	(0.002)
BEV	-2.058	(1.244)	0.732	(0.073)	-12.668	(0.511)	-0.850	(0.083)
PHEV	0.464	(0.711)	-0.028	(0.014)	-0.553	(0.121)	-0.020	(0.063)
Own State	-0.001	(0.247)	0.000	(0.009)	-0.001	(0.057)	0.057	(0.017)
Trend	-0.722	(0.018)	-0.008	(0.000)	-0.018	(0.003)	0.001	(0.001)
PHEV								
Range x PHEV	-2.459	(0.969)	0.257	(0.070)	-0.871	(0.473)	0.153	(0.154)
Cost shifters								
Station Subsidies	0.005	(0.016)	0.000	(0.001)	0.004	(0.004)	0.019	(0.002)
Differentiation IVs								
Price-quadratic-own	0.332	(0.010)	-0.001	(0.000)	-0.006	(0.002)	-0.001	(0.000)
Price-local-own-nest	8.711	(2.129)	-0.918	(0.097)	-4.624	(0.551)	-0.130	(0.086)
Engine-local-own-nest	-11.343	(1.688)	0.091	(0.025)	0.284	(0.140)	0.041	(0.059)
Engine-quadratic-own-nest	-12.897	(0.949)	0.036	(0.008)	0.287	(0.049)	0.048	(0.022)
Engine-local-rival-nest	-4.973	(0.199)	-0.007	(0.002)	0.022	(0.014)	0.009	(0.005)
Acceleration-quadratic-rival	2.276	(0.116)	0.082	(0.007)	0.424	(0.044)	0.001	(0.009)
Acceleration-quadratic-rival-nest	-2.432	(0.138)	-0.086	(0.007)	-0.445	(0.047)	0.001	(0.010)
Footprint-local-own	-0.198	(0.887)	1.116	(0.059)	5.233	(0.337)	0.033	(0.048)
Engine-local-rival	-1.135	(0.205)	-0.112	(0.008)	-0.684	(0.051)	-0.065	(0.027)
EV efficiency-quadratic-rival-nest	0.238	(0.033)	0.005	(0.001)	0.129	(0.007)	0.049	(0.006)
Fuel efficiency-quadratic-own	0.382	(0.110)	-0.005	(0.001)	-0.040	(0.005)	-0.004	(0.002)
PHEV-count-own	0.012	(0.001)	0.000	(0.000)	-0.002	(0.000)	0.000	(0.000)
PHEV range-local-own	-1.459	(0.112)	0.039	(0.003)	0.598	(0.025)	0.146	(0.018)
BEV count-local-rival	-0.156	(0.058)	0.062	(0.005)	1.366	(0.036)	0.088	(0.005)
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	140.664		209.89		96.623		52.472	
Observations	28,288		28,288		28,288		28,288	

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.

Table 9: Kernel density estimation of price sensitivity



B Full demand and supply estimates

Table 10: Full demand and marginal cost estimates

Utility			Marginal Cost		
	Coefficient	SE		Coefficient	SE
Mean Utility			**Range Provision**		
(Intercept)	-9.705	(0.296)	Intercept	0.813	(0.026)
Range	1.772	(0.223)	Trend	-0.070	(0.006)
Range x Trend	-0.118	(0.024)	**Baseline Marginal Cost**		
Stations	0.610	(0.156)	Intercept	1.534	(0.133)
Fuel Cost	-0.281	(0.027)	Weight	0.274	(0.041)
Footprint	0.504	(0.050)	Fuel Efficiency	-0.041	(0.006)
Acceleration	0.295	(0.025)	KW	0.005	(0.000)
Doors	-0.195	(0.027)	Footprint	0.096	(0.019)
BEV	-8.285	(1.539)	BEV	-0.578	(0.043)
PHEV	-5.901	(1.482)	PHEV	0.189	(0.025)
Own State	1.191	(0.072)	2013	-0.011	(0.013)
Trend	-0.114	(0.010)	2014	-0.026	(0.014)
Audi	2.809	(0.087)	2015	-0.057	(0.014)
BMW	3.173	(0.091)	2016	-0.043	(0.014)
Chevrolet	0.468	(0.125)	2017	-0.026	(0.014)
Citroen	0.272	(0.090)	2018	-0.034	(0.014)
Dacia	0.904	(0.164)	Audi	-0.049	(0.052)
Daihatsu	-0.499	(0.175)	BMW	0.028	(0.054)
Dodge	-3.655	(0.305)	Chevrolet	-0.309	(0.068)
Fiat	-0.119	(0.103)	Citroen	-0.153	(0.055)
Ford	1.652	(0.095)	Dacia	-0.843	(0.064)
Honda	1.484	(0.095)	Daihatsu	-0.250	(0.051)
Hyundai	1.536	(0.096)	Dodge	-0.340	(0.093)
Jeep	0.614	(0.107)	Fiat	-0.225	(0.053)
KIA	1.081	(0.092)	Ford	-0.234	(0.055)
Lada	-0.679	(0.188)	Honda	-0.112	(0.056)
Lancia	-1.371	(0.126)	Hyundai	-0.205	(0.054)
Land Rover	1.609	(0.110)	Jeep	-0.151	(0.055)
Mazda	2.170	(0.085)	KIA	-0.242	(0.052)
Mercedes	3.066	(0.096)	Lada	-0.525	(0.063)

Table 10: Demand and marginal cost estimates *(continued)*

	Coefficient	SE		Coefficient	SE
MINI	1.797	(0.252)	Lancia	-0.185	(0.054)
Mitsubishi	1.073	(0.107)	Land Rover	-0.143	(0.053)
Nissan	1.143	(0.103)	Mazda	-0.142	(0.053)
Opel	1.596	(0.095)	Mercedes	-0.048	(0.054)
Peugeot	0.822	(0.090)	MINI	-0.011	(0.062)
Renault	1.447	(0.092)	Mitsubishi	-0.199	(0.060)
SEAT	1.947	(0.100)	Nissan	-0.269	(0.058)
Skoda	2.730	(0.098)	Opel	-0.216	(0.052)
smart	3.22	(0.149)	Peugeot	-0.170	(0.054)
Subaru	0.166	(0.091)	Renault	-0.250	(0.053)
Suzuki	0.96	(0.098)	SEAT	-0.249	(0.052)
Tesla	1.789	(0.465)	Skoda	-0.228	(0.053)
Toyota	1.175	(0.090)	smart	-0.055	(0.102)
Volvo	1.419	(0.090)	Subaru	-0.036	(0.056)
VW	2.971	(0.087)	Suzuki	-0.200	(0.057)
Compact Executive	0.353	(0.099)	Tesla	-0.243	(0.088)
Executive	0.728	(0.155)	Toyota	-0.023	(0.053)
Luxury	1.843	(0.225)	Volvo	-0.088	(0.053)
Mid-size	0.123	(0.049)	VW	-0.133	(0.052)
Coupe	-1.403	(0.139)	Compact Executive	0.270	(0.028)
Station wagon	1.351	(0.137)	Executive	0.259	(0.040)
Roadster	-1.109	(0.140)	Luxury	0.459	(0.048)
Hatchback	1.358	(0.132)	Mid-size	0.159	(0.017)
Sedan	-0.717	(0.135)	Coupe	-0.187	(0.029)
SUV	1.742	(0.120)	Station wagon	-0.246	(0.023)
Van	1.365	(0.128)	Roadster	0.054	(0.041)
ber	-1.079	(0.076)	Hatchback	-0.303	(0.024)
bra	-0.741	(0.070)	Sedan	-0.260	(0.028)
bre	-1.505	(0.123)	SUV	-0.146	(0.024)
bwt	-0.923	(0.094)	Van	-0.214	(0.025)
ham	-0.417	(0.073)			
hes	-0.320	(0.077)			
mvp	-0.608	(0.064)			
nie	-1.064	(0.078)			
nrw	-0.916	(0.094)			

Table 10: Demand and marginal cost estimates *(continued)*

	Coefficient	SE		Coefficient	SE
rlp	-0.857	(0.090)			
sac	-0.372	(0.056)			
san	-1.012	(0.083)			
sar	-0.158	(0.058)			
swh	-1.002	(0.092)			
thr	-0.451	(0.058)			
Interactions					
Price / Income	-5.713	(0.691)			
Standard Dev.					
BHEV	2.563	(0.685)			
Fuel Cost	0.134	(0.017)			

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

C Robustness to alternative corrections

Table 11 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 $s_{\tilde{jmt}} = \frac{\mathcal{M}_{mt}s_{jmt}+1}{\mathcal{M}_{mt}s_{jmt}+J_{mt}+1}$, 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 do not change dramatically across the different corrections.

Table 11: Estimates of key parameters under alternative corrections for zero market shares

	Min bias	**Laplace**	**Naive**
Mean Utility			
Range	1.772	1.694	1.792
	(0.223)	(0.193)	(0.213)
Range x Trend	-0.118	-0.105	-0.116
	(0.024)	(0.023)	(0.023)
Charging Stations	0.61	0.441	0.584
	(0.156)	(0.151)	(0.153)
Fuel Cost	-0.281	-0.263	-0.279
	(0.027)	(0.024)	(0.026)
BEV	-8.285	-5.955	-7.976
	(1.539)	(2.372)	(1.593)
PHEV	-5.901	-3.704	-5.598
	(1.482)	(2.353)	(1.544)
Interactions			
Price / Income	-5.713	-4.172	-5.275
	(0.691)	(0.548)	(0.659)
Standard Dev.			
EV	-2.563	-1.294	-2.368
	(0.685)	(1.798)	(0.743)
Fuel Cost	0.134	0.122	0.13
	(0.017)	(0.015)	(0.017)

Note: Standard errors in parentheses.

D Estimated price elasticities in selected papers

Table 12 presents estimates of price elasticities from several papers using a similar structural model of demand to mine.

Table 12: 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 (Forthcoming)	-5.45
Springel (2020)[3]	[-1, -1.5]
Thurk (2018)	-3.6

Own estimated price elasticity: -3.267
[1] Conlon and Gortmaker (Forthcoming) replication
[2] Conlon and Gortmaker (Forthcoming) 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,

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

we can plug the price FOC into the quality FOC and re-arrange to find

$$c_q = \frac{\partial s(p,q)/\partial q}{|\partial s(p,q)/\partial p|}, \tag{13}$$

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 (13), the larger the level of quality provided in equilibrium.

The effect of a subsidy

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

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

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

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

This gives

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

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

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

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

We can then conclude that

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

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

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 $j = 1, \dots J$ products in a market. Consumers care about the quality of a subset of products $j \in \mathcal{B}$ and do not have any preferences over the quality of the remaining products $j \in \mathcal{I}$.[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.

[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.

The FOCs for product one are then given by

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

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

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

Things become more complicated when we consider an increase on the subsidy of all products in $\mathcal{B}$. We now need to differentiate $J + J_{\mathcal{B}}$ first order conditions ($J_{\mathcal{B}}$ being the cardinality of $\mathcal{B}$). In essence, the effect of price and quality on the FOC of all other products now needs to be taken into account as well.

Let J denote the cardinality of all products, $J_{\mathcal{B}}$ the cardinality of those products with endogenous quality and $f(j)$ the firm of product j. Then, we have the following system of FOCs with

$J + J_q$ equations:

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

$$\vdots$$

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

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

$$\vdots$$

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

The total differentiation of this system yields

$$\begin{bmatrix} \frac{dp_1}{d\lambda} \\ \vdots \\ \frac{dp_J}{d\lambda} \\ \frac{dq_1}{d\lambda} \\ \vdots \\ \frac{dq_{J_\mathcal{B}}}{d\lambda} \end{bmatrix} = \begin{bmatrix} \pi_{f(1)p_1p_1} & \cdots & \pi_{f(J)p_Jp_1} & \pi_{f(1)q_1p_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1p_J} & \cdots & \pi_{f(J)p_Jp_J} & \pi_{f(1)q_1p_J} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_J} \\ \pi_{f(1)p_1q_1} & \cdots & \pi_{f(J)p_Jq_1} & \pi_{f(1)q_1q_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J)p_Jq_{J_\mathcal{B}}} & \pi_{f(1)q_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_{J_\mathcal{B}}} \end{bmatrix}^{-1} \begin{bmatrix} -\pi_{f(1)p_1\lambda} \\ \vdots \\ -\pi_{f(J)p_J\lambda} \\ -\pi_{f(1)q_1\lambda} \\ \vdots \\ -\pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}\lambda} \end{bmatrix}, \qquad (14)$$

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 14 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 14, 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.